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The Impact of the Affordable Care Act: Evidence from California's Hospital Sector†

By Mark Duggan, Atul Gupta, and Emilie Jackson*

We exploit changes in the discontinuity in health insurance coverage at age 65 induced by the implementation of the Affordable Care Act to examine effects on coverage, hospital use, and patient health. We then link these changes to effects on hospital finances. We show that a substantial share of the federally funded Medicaid expansion substituted for existing locally funded safety net programs. Despite this offset, the expansion produced a substantial increase in hospital revenue, reflected in an equivalent increase in operating surplus. We do not detect improvements in patient mortality, although the expansion led to substantially greater hospital and emergency room use. (*JEL* H51, H75, I12, I13, I18, I38)

The 2010 Patient Protection and Affordable Care Act (ACA) led to the largest expansion of publicly funded health insurance coverage since the introduction of Medicare and Medicaid more than 50 years ago. The main provisions of this legislation took effect in January 2014. In states that elected to expand their Medicaid programs as allowed for by the ACA, individuals with family incomes at or below 138 percent of the federal poverty level (FPL) and without another source of coverage could enroll in the means-tested Medicaid program. Those with incomes above this threshold but below 400 percent of the FPL and without another source of coverage could sign up for subsidized private health insurance coverage in ACA mandated exchanges. From 2010 to 2017, the number of Medicaid recipients nationally rose by 18 million, while the number with coverage through the ACA exchanges reached 12 million (Centers for Medicaid and Medicare Services (CMS) 2018).

This intervention offers a unique opportunity to examine the effects of a large expansion of public health insurance in a modern setting. We focus on the state

* Duggan: Stanford University (email: mgduggan@stanford.edu); Gupta: The Wharton School, University of Pennsylvania (email: atulgup@wharton.upenn.edu); Jackson: NBER (email: jacksone@nber.org). Matthew Notowidigdo was coeditor for this article. We would like to thank Abby Alpert; Marion Aouad; Bob Kaestner; Mark Shepard; Jacob Wallace; Laura Wherry; four anonymous referees; and seminar participants at Arizona, Columbia, Johns Hopkins, Stanford, UC-Berkeley, USC, and Wharton along with numerous participants at the AEA, the Annual Health Economics Conference (USC), NBER Public Economics, Midwest Health Economics Conference (OSU), Western Economics Association, and ASHEcon (DC) for helpful comments. We are also grateful to Betty Henderson-Sparks, Aaron Maggetti, Amy Peterson, and Jon Teague of the California Office of Statewide Planning and Health Development for their assistance in providing the hospital/ER discharge data and to Jack Coolbaugh and Catherine Ishitani for excellent research assistance. All remaining errors are our own.

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of California, which elected to expand Medicaid in January 2014.[1] From 2011 to 2016, Medicaid enrollment in the state increased from approximately 8 million to more than 13 million (thus accounting for about one-third of the national increase reported above), and Medicaid spending more than doubled from about $40 billion to $90 billion (Taylor 2017). Additionally, nearly 1.4 million Californians obtained their health insurance through the state's ACA health insurance exchange in 2016, the final year of our study period. We use data on the universe of hospital stays and emergency room (ER) visits in California combined with detailed data on hospital finances from 2008 through 2016. Deploying two complementary research designs, we quantify the effects of the ACA expansions for three key stakeholders—providers, patients, and taxpayers—interpreted through hospital data.

We use a novel empirical approach that exploits the preexisting discontinuity in health insurance coverage at age 65 due to the discrete onset of nearly universal eligibility for Medicare, the public insurer for elderly individuals.[2] This phenomenon has been used by other studies as a quasi-random insurance coverage experiment to examine the effects of Medicare (Card, Dobkin, and Maestas 2008, 2009). The ACA substantially expanded the Medicaid eligibility criteria for nonelderly individuals in California, leading to a large increase in Medicaid coverage for those under the age of 65, as shown in Figure 1, panel A, which plots the fraction of individuals at each age with Medicaid coverage in each year from 2011 through 2016. Because Medicaid eligibility criteria were already fairly broad for those under age 21, and due to nearly universal coverage for Medicare among the elderly population, the effect on Medicaid coverage was greatest for those aged 21 to 64.

The Medicaid expansion, together with the introduction of publicly subsidized private insurance through the ACA exchanges, caused a sharp decrease in the discontinuity in health insurance coverage at age 65, as Figure 1, panel B demonstrates. Our estimation approach compares the pre-post change in outcomes of interest for patients aged 64 (or younger) who experienced an increase in health insurance coverage relative to those 65 and older whose insurance coverage remained essentially unchanged through this entire period. To address potential concerns about spurious trends, we present results from a falsification exercise assuming a placebo expansion in 2010 for all outcomes of interest. Reassuringly, these results indicate no preexisting trends that would bias our results. This regression discontinuity differences-in-difference (RD-DD) approach estimates causal effects most relevant for near-elderly individuals. In a companion set of results, we use the sample of all patients aged 21 to 64 and exploit pre-ACA variation in the population share potentially eligible for Medicaid across geographic markets and find reassuringly similar results.

We begin by examining the changes in payer mix at hospitals. Across different models, we estimate an increase of 6–8 percentage points (pp) in the share of patients

[1] Twenty-four states and Washington, D.C., expanded their Medicaid programs in January 2014. In the 6 years since January 2014, an additional 12 states have expanded or are in the process of expanding Medicaid as called for in the ACA. Many of the remaining 14 states are actively considering expansion.

[2] A small share of individuals who are eligible for Medicaid at age 64 retain Medicaid coverage post-65 because they are eligible for both Medicaid and Medicare, referred to as dual-eligible beneficiaries. Medicare is the primary insurer in these cases.

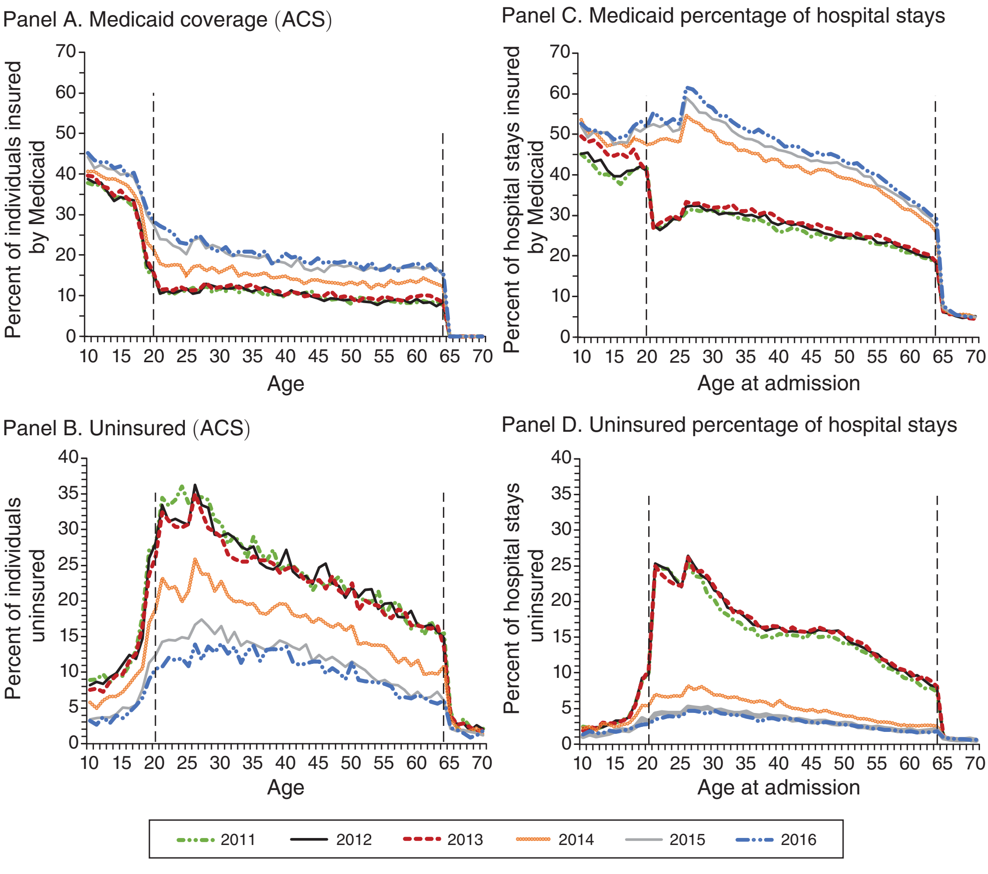

FIGURE 1. INSURANCE COVERAGE TRENDS

Notes: The figure presents parallel sets of plots using American Community Survey (ACS) and hospital discharge data. The figures plot trends in insurance coverage over 2011–2016 for people and hospital patients aged 10–70. Panels A and C present the percentage of individuals and hospital stays, respectively, covered by Medicaid. Panels B and D present corresponding figures for the uninsured (self-pay and county indigent in the discharge data). The vertical black lines highlight ages 21 and 65. The ACS sample has no exclusions. The hospital discharge sample excludes cases related to pregnancy and deliveries, is limited to general acute care hospitals, and excludes individuals residing in zip codes outside of California.

with any form of health insurance coverage. This appears to be driven entirely by an increase in the share of Medicaid patients. We find no net increase in the share of privately insured patients, suggesting that most patients covered by exchange plans already had some form of insurance prior to the ACA. In fact, our RD-DD results indicate minor crowd out of private coverage among patients in their early 60s. Second, we find that about 70–75 percent of the increase in Medicaid replaced hospital care by previously uninsured patients, some of whom would otherwise be subsidized by county-run safety net programs. Since the Medicaid expansion was financed entirely by the federal government in this period, this implies a transfer to California taxpayers who previously financed these safety net programs.

In addition to changes in payer mix, expansion of coverage may lead to greater utilization of hospital care (Finkelstein et al. 2012). We find a net increase of 4–6 percent on average in hospital stays and arrivals at ERs, comparable to the increase in insurance coverage discussed above. In contrast to evidence from the Massachusetts reform (Kolstad and Kowalski 2012; Miller 2012)—and contradicting a key argument for the ACA's insurance expansion—we find a robust, statistically significant increase in ER visits.

Given changes in payer mix and greater utilization, we quantify the effects on hospital finances following the expansion by exploiting pre-ACA variation in the share of uninsured patients across hospitals. Expanding Medicaid coverage likely boosted hospital revenue since Medicaid reimbursed hospitals at higher rates than did uninsured patients—approximately twice as much—as reflected in annual hospital financial data reported to California.[3] We estimate that hospitals received about \$5.4 billion (in 2016 dollars) in additional Medicaid revenue annually due to the expansion. About \$2 billion of this replaced existing hospital revenue from uninsured patients. The net increase of \$3.4 billion is substantial relative to a pre-ACA base of about \$17 billion from Medicaid. We further use our estimates to infer the increase in hospital revenue per reduction in uninsured rates, adding to the growing evidence on this important policy question. We estimate an increase of about \$800 in hospital revenue due to higher Medicaid reimbursement per reduction in uninsured rates, very similar to the value reported by Garthwaite, Gross, and Notowidigdo (2018).

Hospitals may have deployed this additional revenue toward hiring new employees, making capital investments, or offering new services to improve patient care. However, we do not find any statistically or economically significant effects on these inputs. Consistent with this evidence, we find that reported operating surplus increased by an aggregate \$3.4 billion across all hospitals—strikingly similar to the net increase in revenue reported above. Hence, hospitals seem to have accumulated the additional public funds as reserves rather than deploying them toward the production of health care, at least in the short run.[4]

We next investigate whether changes in the utilization of hospital care and improved finances post-ACA lead to improvements in patient health outcomes. Our primary metric of health is in-hospital mortality, and we focus on the subset of patients discharged with highly acute "nondiscretionary" conditions to circumvent selection concerns (Garthwaite et al. 2017). The point estimates imply a meaningful decline in in-hospital mortality post-ACA; however, they are imprecisely estimated. A likely channel for improved health is reallocation of patient care to privately owned

[3] We compute mean reimbursement per discharge for each payer but do not observe reimbursements for individual hospital stays. The mean reimbursement per discharge for uninsured patients likely masks tremendous heterogeneity in payments. A small fraction of wealthy patients may pay the asking rate, while the remaining patients likely pay zero or small amounts

[4] The ACA did influence hospital reimbursement on other dimensions. For example, the ACA reduced the growth rate of Medicare reimbursement rates and intended to reduce the Disproportionate Share Hospital (DSH) program, which differentially aided hospitals serving many low-income patients. However, Congress has repeatedly delayed cuts to DSH spending. The DSH cuts began in fiscal year 2020. More details available at https://cbcny.org/research/dsh-cuts-delayed.

and better-quality hospitals.[5] Pre-ACA, 65-year-olds were significantly more likely than 64-year-olds to receive care at privately owned and better-quality hospitals. But this gap declined by 60 percent on both dimensions post-ACA. We interpret this shift to be demand driven since we find a similar magnitude of switching in ER use, which is less likely to be influenced by insurer networks.

Finally, we tie together our results on utilization and hospital finances and allocate the $5.4 billion in incremental Medicaid spending into four policy relevant buckets. First, we quantify the transfer from federal taxpayers to taxpayers in California. In addition to the replacement of safety net hospital spending, the state also benefited from the improved financial health of publicly owned hospitals, reducing state and local subsidies. Collectively, state taxpayers received about $2 billion (~35 percent) of the additional Medicaid spending. Second, we find that privately owned hospitals received about $1.4 billion (~25 percent) in additional revenue due to greater reimbursements under Medicaid. Third, about $0.8 billion replaced out-of-pocket spending by previously uninsured patients. The remainder (~22 percent) enabled additional care that would not have occurred without the ACA.

Our analysis has three key limitations. First, our results reflect the experience of a specific state that expanded Medicaid. Second, we cannot observe health care delivered outside of the hospital. This precludes testing for improvements in access to preventative and (non-ER) outpatient care, though we find no change in potentially avoidable stays. Third, these results estimate only the short-term effects of the ACA. We acknowledge that the long-term effects, particularly on patient health, may be more substantial.

This paper makes three contributions to the existing literature. First, we highlight the locally funded safety net program in California and use a novel empirical approach to quantify its substitution by Medicaid under the expansion. This aspect has received little attention in previous assessments of the ACA (Sommers, Kenney, and Epstein 2014; Sommers et al. 2016; Courtemanche et al. 2017; Frean, Gruber, and Sommers 2017; and many others), perhaps because safety net programs do not provide traditional health coverage and remain unobserved in surveys. These results also provide empirical evidence to confirm speculation by recent studies (Finkelstein, Hendren, and Luttmer 2019; Finkelstein, Hendren, and Shepard 2019) that Medicaid beneficiaries value the program substantially below cost since it often replaces other parts of the safety net.

Second, we extend existing work on the supply-side effects of the ACA (Blavin 2016; Lindrooth et al. 2018) by quantifying the effects on hospital finances and their (lack of) adjustments to care inputs. By examining changes in both hospital payer mix and finances, we provide an estimate of the transfer from federal taxpayers to hospitals due to higher reimbursement rates. This also relates to recent evidence on the incidence of uninsurance on hospital finances (Garthwaite, Gross, and Notowidigdo 2018).

[5] This channel has previously received little attention, as studies typically valued Medicaid on the basis of improved health or reduced financial risk (Currie and Gruber 1996b; Brevoort, Grodzicki, and Hackmann 2017; Goodman-Bacon 2018; Gallagher, Gopalan, and Grinstein-Weiss 2019).

Third, we extend the literature examining the effects of insurance coverage by providing evidence from an extremely large natural experiment. Randomized field experiments are the gold standard in causal inference; however, their limited scale precludes studying general equilibrium effects. For example, the Oregon Health Insurance Experiment (Finkelstein et al. 2012) randomized the expansion of Medicaid to 10,000 new beneficiaries. In comparison, California added nearly five million Medicaid beneficiaries due to the ACA. Our results differ from those of the Oregon experiment in two ways. First, our implied IV estimate of the increase in hospital stays due to insurance coverage is nearly three times as large as theirs. This highlights the potentially large magnitude of general equilibrium effects even in the short run, likely through supply-side responses by hospitals and physicians. Intuitively, our estimates are about half as large as comparable estimates of the long-term effects of Medicare (Finkelstein 2007). Second, we show that access to coverage also led to changes in hospital choice, with privately owned and higher-quality hospitals gaining share.[6] This could be an intermediating mechanism leading to improved patient health.

Our results take on additional significance when one considers state decision-making regarding the Medicaid expansion, which, as a result of a 2012 Supreme Court decision, was left up to the states rather than mandated by the federal government and will soon be considered by the Supreme Court again. Evidence regarding the effects of this expansion on insurance coverage, quality of care, and hospital finances along with state and local spending on health care can be helpful to states in assessing whether to expand public insurance.

The rest of the paper is structured as follows. Section I provides background on insurance coverage in California and the insurance provisions of the ACA. Section II describes our data and presents descriptive statistics. Section III describes the empirical strategy for the RD-DD approach and presents our empirical results. Section IV presents results for changes in hospital finances. Section V presents a decomposition of incremental federal Medicaid spending into transfers to patients, hospitals, and taxpayers. Section VI concludes.

I. Background

A. *Insurance Coverage Pre-ACA*

The health insurance landscape prior to 2014 was characterized by relatively high uninsurance rates among specific subgroups. As recorded in the ACS, the pre-ACA uninsurance rate in California among nonelderly adults aged 21–64 was 3 times that of the remaining population (25 percent versus 8 percent). The elderly benefited from nearly universal coverage provided by Medicare, while a large fraction of children were covered by Medicaid (nearly 40 percent).

[6] Our results extend previous work that has focused on specific categories of care, such as ER use (Barakat et al. 2017; Garthwaite et al. 2017; and Nikpay et al. 2017), drug prescriptions (Ghosh, Simon, and Sommers 2017), or patients with specific diseases (Anderson et al. 2016), or has used survey data to examine effects on health outcomes (Courtemanche et al. 2018).

In some states, providers were reimbursed by locally administered safety net programs for hospital care provided to some low-income individuals ineligible for Medicaid. Hadley et al. (2008) estimates that about 20 percent of total spending on the uninsured, or about $11 billion, was covered by such local programs in 2008. This is particularly important in our setting since California counties are legally bound to provide such a safety net. In California, safety net programs were funded primarily through a mix of state and county general funds.[7] Throughout the paper, we use the terms safety net and county indigent program interchangeably.

Each county designed its indigent services program, resulting in substantial variation in eligibility requirements (e.g., income, assets, residence, age, medical need, and immigration status) and services covered (California Health Care Foundation 2009).[8] Prior to the passage of the ACA, California spent approximately $2 billion annually to care for the uninsured through the Medically Indigent Services Program, which provided care in 24 mostly urban counties, and the County Medical Services Program, which operated in 34 predominantly rural counties (Council of Economic Advisers 2009). Note that only nonelderly adults were eligible for these safety net programs in California. These programs were primarily aimed at helping providers maintain solvency and did not provide traditional risk protection to individuals. Accordingly, people who transitioned from county programs to Medi-Cal gained formal insurance coverage and access to a wider network of providers.

Reimbursing care utilized by low-income individuals through counties or other locally financed mechanisms extended beyond California. Several other states—including those that did not expand Medicaid—offered variants of such programs. Examples include Colorado, Florida, Idaho, Indiana, Massachusetts, Michigan, New Jersey, Texas, New Mexico, Pennsylvania, and Louisiana.[9]

B. *The Affordable Care Act*

The ACA expanded access to health insurance primarily through two channels, both of which became effective on January 1, 2014. First, in all states, individuals in families with incomes between 100 and 400 percent of the FPL who were not already eligible for health insurance, either from an employer or from Medicaid, were now eligible for premium subsidies to purchase private health insurance on exchanges. Second, the ACA authorized expansion of Medicaid eligibility to all individuals without another source of coverage with family incomes below 133 percent of the FPL. California is one of the original 25 states (including D.C.) that

[7] Federal funding through DSH funds played a small role (Taylor 2013).

[8] Notably, while undocumented immigrants are not eligible for Medicaid, a number of county programs provided some degree of coverage to this group. As each county designed its own program, the scope of coverage varied. For example, San Francisco provides full services, while Los Angeles provides no services, and many counties only provided emergency services.

[9] Louisiana offered free health care for low-income individuals not on Medicaid at state-owned safety net hospitals. See https://www.kff.org/health-reform/fact-sheet/the-louisiana-health-care-landscape/. For more information on the Colorado state program, see https://www.colorado.gov/pacific/hcpf/colorado-indigent-care-program. Some other states have indigent care programs that are mainly funded through disproportionate share payments, e.g., Georgia and New York. See https://www.communitycatalyst.org/initiatives-and-issues/initiatives/hospital-accountability-project/free-care/states for an exhaustive description of indigent coverage for hospital care.

chose to expand Medicaid in January 2014.[10] The Congressional Budget Office estimated that the ACA insurance expansions directly cost the federal government \$120 billion in 2017 (Congressional Budget Office 2017). Gallup and Sharecare surveys show that the percentage of adults without health insurance peaked around 18 percent in late 2013 and then sharply dropped to 11 percent by the beginning of 2016. Frean, Gruber, and Sommers (2017) estimate that about 60 percent of this observed decline was due to these two channels.

Even among states that chose to expand Medicaid, there is substantial variation in the impact on Medicaid enrollment, driven by variation in baseline enrollment due to states' initial generosity in eligibility criteria and differences in the socioeconomic composition of states. Online Appendix Figure A.1a highlights this variation across states by presenting the percentage of the state population enrolled in Medicaid in 2013:III and the net change in enrollment through October 2016. Medicaid covered about 20 percent of California's population in 2013, and it experienced an increase of 11 percentage points. The chart also shows that California is not an outlier among the expansion states, with several others experiencing even larger increases. Figure A.1b further demonstrates that the relative decline in uninsurance among low-income individuals in California was only modestly greater than average (indicated by the red line). This evidence suggests that California serves as a reasonable case study to represent the effects of the ACA in states that expanded their Medicaid programs. This is consistent with the findings from other studies; for example, Garthwaite et al. (2019) show that the effects of the ACA on hospital utilization in California are similar to and statistically indistinguishable from the average effect across 11 initial-expansion states.[11]

C. *Age-Based Discontinuities in Public Insurance*

Public insurance programs commonly use age-based thresholds to determine eligibility. For example, individuals can enroll in Medicare when they turn 65, but not earlier, unless they are enrolled in the Social Security Disability Insurance program or have end-stage renal disease. Similarly, children enjoy relatively generous eligibility rules under Medicaid until age 18 (or older under some circumstances) but then lose coverage because the eligibility criteria become more restrictive. Prior to the ACA, adults aged 21 to 64 were generally ineligible for Medicaid in California except in the case of pregnancy, nursing home residence, or enrollment in the federal Supplemental Security Income program. This helped to create discontinuities in insurance coverage at the ages of 21 and 65 in California.[12]

[10] California took advantage of a Section 1115 waiver to expand Medicaid access early to low-income childless adults. This "early expansion" started in July 2011 and expanded gradually county by county. Through 2013, California had enrolled about 515,000 individuals into Medicaid across 43 counties, of which about 60,000 were transferred from other safety net programs (Sommers, Kenney, and Epstein 2014). This is small relative to the 3.6 million and 1.3 million individuals enrolled in Medicaid and the ACA exchange, respectively, over January 2014 through June 2016.

[11] They examine effects of the ACA on hospital stays and ER visits in New Jersey, Ohio, Connecticut, Maryland, New York, Wisconsin, California, Iowa, Rhode Island, Minnesota, and Arizona. See Figures 16–18 on pages 72–74.

[12] Welfare recipients and disabled individuals were relatively generously covered by Medicaid. However, only individuals aged less than 21 could enroll based on low-income status ("medically indigent person or family"). An

To examine the impact of these eligibility restrictions on coverage, we turn to the ACS using data from California.[13] Figure 1, panel A presents the share of individuals who reported Medicaid coverage at each age from 10 to 70 during 2011–2016. In the pre-ACA period (2011–2013), Medicaid coverage was high for children of age 10 (40 percent) and gradually declined until age 17. Between ages 17 and 21, it fell nearly linearly by about 20 percentage points, without a large discontinuity at any one age. In the post-ACA period (2014–2016), individuals throughout this interval gained Medicaid coverage, but individuals older than 18 benefited more from the relaxation of eligibility restrictions—the drop between ages 17 and 21 declined in magnitude to about 15 pp. In contrast, the eligibility restriction at age 65 manifested pre-ACA in a sharp drop in Medicaid coverage of about 8 pp, which increased to 14 pp in the post-ACA period since more 64-year-olds became eligible for Medicaid.

Figure 1, panel B (note the expanded scale) presents the percentage of individuals that lacked health insurance coverage, as recorded in the ACS. This plot noticeably flips the pattern seen in the previous plot. Pre-ACA, there was an increase of about 20 pp in uninsurance between ages 17 and 21, suggesting that the Medicaid eligibility restrictions were important. At age 65, there was a discontinuous decline in uninsurance of about 15 pp due to the onset of Medicare. Post-ACA, the shifts in uninsurance at these ages diminish in magnitude, indicating that the ACA expansions were effective in increasing coverage for nonelderly adults. Note that there is no change in the share of Medicaid or uninsurance at ages 65 and above throughout this period, suggesting that this group was unaffected by the ACA's coverage changes.

This evidence confirms a sharp discontinuity in Medicaid and uninsurance at age 65. The interaction with the ACA expansions motivates our use of a regression-discontinuity-based research design at this threshold to examine the effects of the ACA on a variety of outcomes. On the other hand, the change in coverage in the ACS data appears to be much more gradual at age 21.

II. Data

We have two main administrative data sources—patient-level hospital discharge data and annual files on hospital finances. We use the universe of hospital inpatient stays and ER visits at nonfederal hospitals in the state of California for the period 2008 through 2016, obtained from California's Office of Statewide Health, Planning, and Development (OSHPD). These confidential data include approximately 3.8

example of pre-ACA eligibility restrictions in California in 2007 is available at http://www.dhcs.ca.gov/formsandpubs/forms/Forms/MCED/Info_Notice/MC002_ENG_0907.pdf. Childless adults were usually ruled out unless they had special circumstances such as pregnancy or were in a nursing home.

[13] The ACS permits respondents to claim coverage through multiple health insurers. To make the ACS more comparable to the hospital discharge data where we observe only the primary payer, we apply some simple rules to identify the primary payer. Medicare is always assumed to be the primary payer regardless of any other insurer. Next, we consider Medicaid as the primary payer if it is flagged as an insurer. Next, we consider other government programs such as Tricare, Veterans Affairs, and Indian Health Services as primary payers. Next, we consider private nongroup and, finally, employer-sponsored insurance as the primary payer. Individuals without any of these payers are considered to be uninsured. These primary payer categories are defined to add to 1.

million hospital discharges and 11 million ER visits each year. Each observation pertains to a hospital stay or ER visit and provides information on the hospital, dates of service, patients' primary insurer type and basic demographics, a vector of up to 25 diagnoses and procedure codes, and patient zip code of residence. As is standard in such files, if an ER visit subsequently leads to hospitalization, then it only appears as a hospital discharge, though the record indicates whether the stay originated as an ER visit. Crucially, we observe both a patient's birth date and admission date, and hence, we can precisely calculate a patient's age at admission. The hospital financial data provides annual information on revenues and patient volume by payer along with aggregate hospital-level data on expenditure by category.

We impose three restrictions when constructing our analysis sample from the discharge data. First, we focus our attention on short-term general acute care hospitals to decrease the likelihood of small specialty hospitals (for example, rehabilitation or long-term care) influencing the results. This restriction decreases the number of hospitals from 450 to 370 but retains 95 percent of hospital stays and nearly all ER visits. Second, since California Medicaid eligibility rules were already generous regarding pregnancy and newborn delivery cases before the implementation of the ACA, we exclude pregnancy-related hospital stays and ER visits from the analysis. Third, we exclude patients residing outside of California or with missing zip codes of residence.[14]

We exclude the years 2008–2010 from our main analyses, reserving them for falsification exercises or to compute measures of pre-ACA variation. Our main sample therefore spans 2011–2016, three years before and after the ACA expansion. We organize recorded insurance coverage into five categories—Medicaid, private, miscellaneous, self-pay, and county. Miscellaneous is primarily composed of Medicare but also includes workers' compensation and government employee plans. Both of the last two categories pertain to uninsured patients, with a subtle difference. Self-pay includes charity cases and those who pay for their care themselves, while county refers to patients whose care was covered by one of the county indigent programs described above.

Figure 1 presents the share of hospital admissions in each of these years that were covered by Medicaid (panel C) and uninsured (panel D) respectively. To facilitate comparison, these figures are presented alongside figures using ACS data, which reflect population-level means. The patterns are very similar at age 65 but differ at age 21. Pre-ACA, there is a sharp decrease in Medicaid coverage at age 21 among hospital patients, but not in the ACS. Post-ACA, there is a larger relative increase in Medicaid coverage among 21-year-old hospital patients than in the population. These discrepancies could occur for two reasons: first, if uninsured ACS respondents aged 17–20 were likely Medicaid eligible and enrolled by hospitals during their stay and, second, if newly eligible 21-year-old Medicaid beneficiaries were sicker than the average, we would see a sharper increase in the share of Medicaid hospital patients at age 21 post-ACA. Nonetheless, in light of this difference between the

[14] Approximately 1.7 percent of the discharge records over 2008–2016 were for patients having either an out-of-state or missing zip code.

ACS and our discharge data, we focus our RD-DD analysis at the age 65 threshold, presenting results for young adult patients in online Appendix B.

A. *RD-DD Sample*

In our preferred specifications, we limit the sample to patients admitted within 12 months of their sixty-fifth birthday. In order to minimize measurement error, we exclude individuals who arrived at the hospital within 15 days of becoming eligible for Medicare.[15] In robustness checks, we explore the sensitivity of our results to using larger age bandwidths. Focusing on specific age groups dramatically curtails the sample size, leaving approximately 560,000 hospital stays and 1.35 million ER arrivals for the 64–65 group (henceforth, elderly patients). ER arrivals include both ER visits and hospital stays that originated in the ER. Throughout the paper, we prefer to analyze the sample of ER arrivals since it enables analysis without conditioning on hospital admission decisions that could change in response to the ACA.

Table 1, panel A summarizes descriptive statistics on the main RD-DD analysis sample of hospital stays and ER arrivals. The table highlights the sharp increase in Medicaid's share of discharges and the corresponding decrease in uninsurance for patients in this age group. We compute utilization rates as hospital stays and ER arrivals per 1,000 people per year using California population estimates by single year of age. This normalization is often used to account for differences in population levels across ages (e.g., there were about 10,000 more 64-year-olds than 65-year-olds in California in 2013). It is even more important in this setting since the size of the relevant cohorts changed at different rates during this period.[16] We use in-hospital mortality as our metric of patient health.

B. *All Nonelderly Adults*

We supplement the RD-DD results using a larger sample of all nonelderly adults (ages 21–64) and exploit baseline variation in poverty rates across geographic markets. We use hospital service areas (HSAs) as our unit of analysis; this is similar to the approach used in other studies that leverage geographic variation in baseline rates of coverage (Finkelstein 2007; Courtemanche et al. 2017; Frean, Gruber, and Sommers 2017; Duggan, Goda, and Jackson 2019).[17] HSAs are defined as "collections of contiguous zip codes whose residents receive most of their hospitalizations

[15] Individuals are eligible for Medicare starting on the first day of the month in which they turn 65. Accordingly, we use this as the threshold date instead of the birthdate.

[16] We obtained California population estimates for 2011–2016 from the National Cancer Institute/National Institutes of Health. They generated these estimates from population data provided by the National Center for Health Statistics. More information is available at https://seer.cancer.gov/popdata/singleages.html. These estimates show that the number of 65-year-olds grew by ~9 percent (33,000) over 2014–2016 versus 2011–2013, while the corresponding increase for 64-year-olds was only ~4 percent (15,000). Hence, looking at absolute changes in patient volume could be misleading.

[17] HSAs were defined by the Dartmouth Atlas Project. There are 209 HSAs in California, of which 79 and 34 are in the Los Angeles and San Francisco metropolitan regions, respectively. In comparison, there are 58 counties and approximately 1,800 zip codes.

Table 1—Summary Statistics

Panel A. RD-DD sample (ages 64–65)	Hospital stays		ER arrivals	
	2011–2013	2014–2016	2011–2013	2014–2016
All observations	277,158	281,062	607,997	732,971
Admitted through ER	169,819	180,273	N/A	N/A
Medicaid	12.6	17.8	12.2	19.7
Private	30.0	27.6	29.4	27.1
Uninsured	4.5	1.6	9.6	4.3
County	1.8	0.2	2.7	0.5
Self-pay	2.6	1.4	6.9	3.8
Utilization per 1,000 population	135	128	294	333
Government hospital	11.4	11.2	15.6	14.7
In-hospital mortality	2.6	2.7	1.2	1.0
In-hospital mortality (nondiscretionary)	3.6	3.0	1.9	1.5
Panel B. Nonelderly sample (ages 21–64)	Hospital stays		ER arrivals	
	2011–2013	2014–2016	2011–2013	2014–2016
Discharges	3,791,199	3,737,040	18,579,073	21,730,908
Nondiscretionary	404,029	387,173	1,074,743	1,148,198
Medicaid	25.3	40.9	24.4	43.2
Private	38.9	35.6	34.6	32.4
Uninsured	14.4	3.4	26.6	11.2
County	5.8	0.4	5.4	0.9
Self-pay	8.6	2.9	21.2	10.4
Government hospital	15.8	14.7	18.5	16.5
Mortality (full sample)	1.60	1.64	0.35	0.30
Mortality (nondiscretionary)	2.22	2.03	0.83	0.68
Panel C. Hospital finances ('000\$/bed)	2011–2013	2014–2016	Change	
Licensed beds	234	230	−2%	
Total patient revenue	968	1,100	14%	
Private	411	447	9%	
Medicare	329	352	7%	
Medicaid	192	283	47%	
County	12	2	−81%	
Self-pay	24	15	−38%	
Capital spending	82	70	−15%	
Total payroll	379	407	7%	
Operating margin	39	63	60%	

Notes: This table presents descriptive statistics from the samples used in the main analyses of the paper. Panels A and B present statistics for the samples in the RD analysis and geographic analysis, respectively. Fraction uninsured includes patients coded as self-pay or county indigent coverage. Panel A focuses on cases pertaining to ages 64–65, where ages are recorded at the time of admission. ER arrivals include ER visits and hospital stays that originated in the ER. To calculate utilization, we normalize number of annual stays/ER arrivals by the population in relevant age-year cell obtained from the National Cancer Institute; hence, these are measures of utilization per 1,000 people per year. Government hospitals include city, county, and district but not federally owned hospitals. We present in-hospital mortality for the full sample as well as for the sample of patients discharged with nondiscretionary cases (i.e., conditions like heart attack, fractures, etc.) for which patients cannot avoid hospital care. Panel C presents data on hospital finances. All revenue and expenditure variables are expressed in thousands of 2016 dollars per bed. Operating margin is the difference between operating revenue and expenses.

from hospitals in that area." There are 209 HSAs in California, and on average, an HSA is smaller than a county but much larger than a zip code. Table 1, panel B presents summary statistics on this sample. To be consistent with the RD-DD analysis, we exclude the 2008–2010 period. The resulting analysis sample has 7.5 million and 40.3 million hospital stays and ER arrivals, respectively.

C. *Hospital Finances*

We use hospital financial files covering 2011–16. The financial data are available for a smaller number of hospitals (about 320 instead of 370) since Kaiser Permanente and some other hospitals do not report their finances individually.[18] We make two transformations to the data in preparation for our analysis. First, we convert all nominal values into 2016 dollars using the consumer price index for urban consumers (CPI-U). Second, we normalize revenue, operating surplus, capital spending, and discharges by the hospital's average number of licensed beds between 2008 and 2010 to eliminate variation due to hospital size.

Table 1, panel C presents descriptive statistics on the key variables used in the pre-ACA and post-ACA period. The average hospital in our sample has about 230 beds and receives about $1 million in total patient revenue per bed per year. The large increase in the share of patients with Medicaid coverage observed in the discharge data are also reflected in the financial data—Medicaid's share of total revenue increased from about 20 percent before the ACA to 26 percent post-ACA.

III. Effects on Insurance, Utilization, and Health

A. *Empirical Strategy*

Consider a conceptual reduced form model of the effect of health insurance coverage on outcome Y as below:

$$Y_i = \alpha + \beta \cdot Ins_i + \epsilon_i. \tag{1}$$

The variable Y_i denotes an outcome of interest (e.g., utilization of care) for individual i, and Ins_i is an indicator set to 1 if the individual has health insurance coverage and 0 otherwise. The ϵ_i term represents all unobserved factors that affect outcome Y_i. The key challenge in obtaining an unbiased estimate of the causal effect β is that individuals choose to purchase or enroll in health insurance coverage based at least partly on private information about their health risk and appetite for risk—factors that the econometrician cannot observe. Online Appendix Table A.1 illustrates this self-selection problem by presenting key attributes for insured and uninsured individuals at ages 20–21 (panel A) and 64–65 (panel B) using 2004–2009 data from the National Health Interview Survey (NHIS). For example, insured elderly are more likely to be married or employed but less likely to be smokers. The differences (column 3) are both statistically significant and economically meaningful. These individuals are likely to differ on important unobservable characteristics as well, implying that the required condition $\mathbb{E}(\epsilon_i | Ins_i) = 0$ will not be not satisfied.

Recent studies (Card, Dobkin, and Maestas 2008, 2009; Anderson, Dobkin, and Gross 2012, 2014) have overcome this endogeneity concern by exploiting the

[18] Kaiser Permanente is a large, vertically integrated payer and health system in California owning about 35 hospitals. Individual medical centers within Kaiser do not report financial results publicly. In addition, some state-owned and private hospitals are also not deemed "comparable" by OSHPD, and as a result, they do not report finances.

presence of age-based insurance eligibility restrictions and discontinuities in coverage by using a fuzzy regression discontinuity (RD) framework. For example, in our setting, we can exploit the discontinuous change in insurance coverage that existed pre-ACA at age 65 (shown in Figure 1, panel B) to determine the causal effect of insurance coverage. We build on the prior literature by exploiting the fact that the Medicaid expansion and introduction of the insurance exchange led to dramatic changes in the discontinuity in insurance coverage at specific ages. More specifically, we interact the RD framework with a differences-in-difference design. Accordingly, we propose the estimating equations

$$Ins_{it} = \alpha_{10} + \delta_{1t} + \theta_{11} d_i + \theta_{12} d_i \cdot T_t + \lambda_{11} \bar{a}_i + \lambda_{12} \bar{a}_i \cdot d_i + \left[\mathbf{X}_i' \psi_1 +\right] \epsilon_{1it}, \tag{2a}$$

$$Y_{it} = \alpha_{20} + \delta_{2t} + \theta_{21} d_i + \theta_{22} d_i \cdot T_t + \lambda_{21} \bar{a}_i + \lambda_{22} \bar{a}_i \cdot d_i + \left[\mathbf{X}_i' \psi_2 +\right] \epsilon_{2it}. \tag{2b}$$

Equation (2a) represents the first-stage equation estimating the pre-ACA discontinuity in insurance coverage at the threshold (θ_{11}) and the change in this discontinuity post-ACA (θ_{12}). We define $d_i = \mathbf{1}(a_i < 65)$ for the elderly to denote those aged 64 or younger. The indicator $T_t = \mathbf{1}(t \geq 2014)$ denotes whether the ACA has been implemented. We de-mean patient age relative to the benchmark, which we denote $\bar{a}_i$, and include a full set of year fixed effects δ_t. For some outcomes, we also include a vector of patient controls $\mathbf{X}_i$ to account for observable differences in patient sickness, such as arrival diagnosis category and gender.

In our main specification, we use a linear polynomial in age, allowing different slopes for individuals above and below the threshold but constant over time. In robustness checks, we further relax this structure and allow the slopes to vary pre- and post-ACA as well. We cluster standard errors by day-of-age cells (e.g., 65 and 20 days, 65 and 21 days, and so on) to account for possible correlated error terms among patients of the same day of age. Equation (2b) presents the corresponding reduced form equation modeling the effects on the outcome Y_i.

This strategy can be used to recover two types of estimators. The first estimator is the average change in discontinuity at the threshold post-ACA (θ_{12} and θ_{22}), which captures the reduced form change in insurance coverage, utilization, or health caused by the ACA. Since these are similar to differences-in-difference estimators, the identification assumption is that in the absence of the ACA insurance expansions, there would be no change to the discontinuity that existed pre-ACA, i.e., $\theta_{12} = 0$ and $\theta_{22} = 0$. We present supporting evidence through a falsification exercise assuming a placebo insurance expansion in 2010. We find little or no change in any outcome of interest between 2008–2009 and 2010–2011, providing reassuring evidence in support of this assumption.

The RD-DD IV estimator $\gamma_{RD,DD} = \theta_{22}/\theta_{12}$ (Persson 2020) captures the causal effects of insurance coverage on other outcomes and estimates a local average treatment effect, or LATE (Hahn, Todd, and Van der Klaauw 2001; Lee and Lemieux 2010). Two identification assumptions merit discussion. First, relevant observable and unobservable factors that could affect the outcomes of interest should vary smoothly at the age threshold. For example, if individuals are disproportionately likely to exit the labor force exactly at age 65, this would violate the above assumption. Online Appendix Table A.1, column 5 presents population-weighted estimates from the NHIS on discontinuities in marital status, employment, and other factors at ages 21 (panel A) and 65 (panel B). The evidence reassuringly indicates that there is no statistically significant jump in these factors—with the exception of alcohol consumption, which jumps at age 21.

The second assumption is the exclusion restriction, i.e., reduced form effects on utilization and health are only due to change in behavior by "compliers," those gaining insurance due to the ACA. Note that in this setting, there are two types of compliers representing two different mechanisms: individuals gaining coverage for the first time due to the ACA (previously, self-pay) and those without formal coverage but for whom some care was reimbursed (previously, county) who are now switching to Medicaid or an exchange plan. Since we have only one instrument, we cannot distinguish between these channels. Further, some of the reduced form effect may be contributed by individuals switching from private coverage to Medicaid post-ACA. Card, Dobkin, and Maestas (2009) note a similar caveat in their interpretation of the effects of Medicare coverage on mortality.

Insurance coverage makes the use of hospital care more likely (Manning et al. 1987; Finkelstein et al. 2012), and hence, estimates of changes in payer shares obtained using discharge data could be biased. This approach underestimates the sharp increase in uninsurance at age 64 (θ_{11}), since some uninsured 64-year-olds are "missing" in the discharge data.[19] Figure 1, panels B and D illustrate this bias—the pre-ACA discontinuity in uninsurance appears to be about 12 pp in the ACS but is only 7 pp in the discharge data. Whether this also leads to bias in the estimated *change* in discontinuity (θ_{12}) is unclear and depends on how the uninsured respond when they gain coverage post-ACA. A downward-biased first-stage estimate assumes greater significance in the context of IV analysis since it will tend to bias the RD-DD estimates upward. Note that the reduced form estimates of effects of the ACA expansion on hospital utilization and hospital mortality are still valid since we observe the universe of hospital discharges and ER visits.

We address this concern in two ways. First, we replicate this analysis using ACS data from California. Since the ACS is designed to be nationally representative, it helps estimate population-level changes in insurance coverage due to the ACA. However, it also has two limitations. First, it does not have data on respondent birth date or month, and hence, the RD-DD specifications are relatively crude. Second, while the ACS faithfully captures the aggregate increase in the population share having any insurance, details on changes in the shares of specific payers are less credible. For example, it likely underestimates the Medicaid share due to underreporting by respondents (Klerman, Ringel and Roth 2005; Meyer, Mok, and Sullivan 2009). It follows that the ACS is less useful when examining crowd out.

Hence, we also replicate the analysis using a subset of the discharge data for patients who were admitted with nondiscretionary conditions requiring immediate

[19] To see the source of the bias, consider how the RD estimator is computed. To a first order, $\theta_{11} = (I_{64}/Y_{64}) - (I_{65}/Y_{65})$, where I_{64} and Y_{64} denote the number of 64-year-old patients with insurance coverage and total patients, respectively, all in the pre-ACA period. However, Y_{64} is suppressed downward since more 64-year-olds are uninsured and, therefore, less likely to use hospital care. The first term is, therefore, biased upward, leading to an underestimate of the decrease in coverage at age 64.

hospital care.[20] These are so named since previous literature (Garthwaite et al. 2017; Garthwaite et al. 2019) has validated that hospital utilization for these conditions is largely unaffected by insurance coverage and convenience, mitigating the key concern of bias due to missing uninsured patients. Indeed, we also find only small utilization effects at age 64 for these conditions. Therefore, we have more confidence that changes in payer shares quantified using this subset are much less contaminated by any changes in utilization. A limitation of this exercise is the dramatic decrease in sample size—only about 10 percent of hospital stays (and a smaller fraction of ER visits) are nondiscretionary in our sample. Taken together, these exercises help us to assess the magnitude of the bias in the first-stage estimates of the change in the share insured and provide lower bounds for the effects on utilization and health.

B. *Hospital Payer Mix*

We begin by analyzing changes in the share of patients with insurance, i.e., patients with private coverage, Medicaid, or miscellaneous, as defined in Section II. We then investigate changes in the shares of specific payers.

Change in the Share Insured.—Figure 2 plots observed and predicted changes in the share of patients with health insurance in 2014–2016 relative to 2011–2013 (circles, solid lines) for elderly patients. The predicted values were obtained by estimating equation (2a) on case-level data, although for presentation clarity, we collapse the data to month of age.[21] The share of insured patients increased differentially for 64-year-olds post-ACA by about 6 pp. One approach to interpret the magnitude of this change is to compare it to the pre-ACA gap in the share of insured between the treated and "control" patient groups, since 64-year-olds have historically had lower coverage relative to their counterparts aged 65 (Card, Dobkin, and Maestas 2008). The pre-ACA gap (not presented in the figure) was about 7 pp. Hence, the ACA nearly eliminated the disparity in insurance coverage at age 65, which is also suggested by the patterns in Figure 1, panel D.

Table 2 presents the corresponding estimates of the changes in payer shares around age 65, obtained by estimating equation (2a). Panels A (main sample) and B (nondiscretionary sample) present estimates obtained using the discharge data, while panel C presents estimates using regressions on ACS data, incorporating survey weights. The coefficient in panel A, column 4 estimates the change in the share insured and corresponds to the plot in Figure 2 discussed above.

[20] We followed Garthwaite et al. (2017) to identify nondiscretionary cases. They provide the conditions and International Classification of Diseases, Ninth Revision (ICD 9) codes used to define this group. We extend their work by identifying the matching International Classification of Diseases, Tenth Revision (ICD 10) codes to apply to 2015–2016 data. We exclude sepsis from this exercise since there is no singular matching ICD 10 code for the ICD 9 code 995.91.

[21] We use regression coefficients from equation (2a) to predict the probability of insurance coverage for each patient. We then collapse these predicted probabilities by taking the mean across all patients admitted with the same month of age. For both predicted and observed values, we calculate differences between the pre-ACA and post-ACA period in each month-of-age cell. The figures plot these aggregated predicted—and corresponding observed—values.

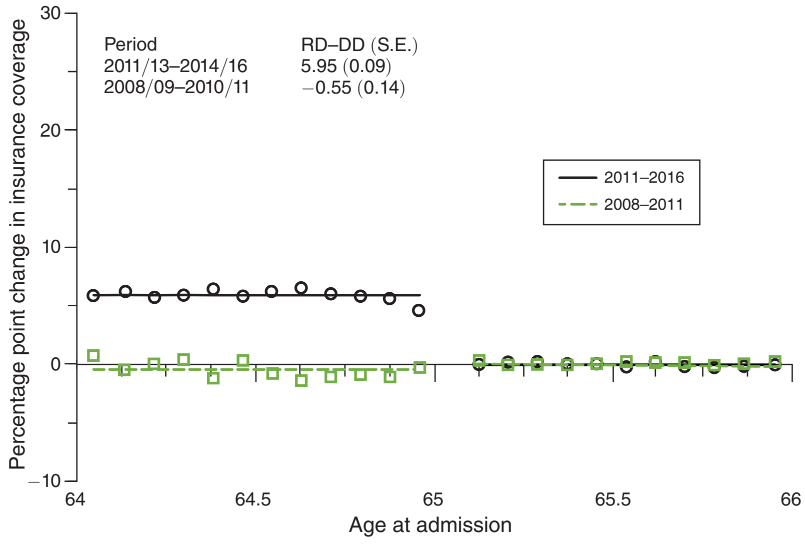

Figure 2. Insurance Coverage

Notes: This figure presents the percentage point change in insurance coverage among hospital patients and corresponding fitted values by month of age. These were obtained by estimating equation (2a) on discharge-level data, as described in Section IIIA, for the sample of patients aged 64–65. The treated groups are those aged 64. The figure presents results for 2011–2016 (circles, solid line), and results from 2008 to 2011 (squares, dashed line), which serves as a falsification exercise. The dependent variable—insurance coverage—is defined by the patient having private, Medicaid, or miscellaneous coverage, and values are either 0 or 100. All models control linearly for age and include year fixed effects. To improve presentation, we collapse the data to month-of-age cells. We also note the estimated change in discontinuity, which is the coefficient on $d_i \cdot T_t$ in equation (2a). Standard errors are clustered by day-of-age cell.

When we focus only on nondiscretionary cases (panel B), we estimate an increase in the share insured of 8 pp, about one-third larger in magnitude (estimated with wider confidence intervals due to the smaller sample size). However, the corresponding estimate using ACS data is about 6.6 pp, with robustness checks in online Appendix Table A.2 indicating that estimates using different specifications and/or bandwidths are centered around 6 pp. Taken together, we conclude that the main coefficient may not necessarily understate the increase in share with insurance due to the ACA and, if so, perhaps does so only moderately. Nevertheless, we present results using the nondiscretionary sample for all outcomes.

Figure 2 also presents—as a falsification exercise—the corresponding observed and predicted changes in insurance coverage over 2010–2011 relative to 2008–2009 (squares, dashed lines). The estimated coefficient is an order of magnitude smaller and of the opposite sign: −0.6 pp. In addition to being minor, this estimate implies a differential pretrend of decreasing insurance coverage among those aged 64, which would work against us finding an increase in health insurance coverage for this group post-ACA.

Crowd Out.—An important policy concern associated with the expansion of publicly funded insurance is the potential crowd out of existing payers. Our research design is well suited to identify crowd out of existing payers for hospital patients.

Table 2—Hospital Payer Mix

	Medicaid (1)	Private (2)	Misc (3)	Insured (4)	County (5)	Self-pay (6)
Panel A. All stays						
Age 64 × post	8.66	−2.61	−0.09	5.95	−3.32	−2.64
	(0.18)	(0.24)	(0.24)	(0.09)	(0.05)	(0.08)
2011–2013 mean (age 64)	18.87	43.01	30.02	91.9	3.56	4.54
Observations	558,220					
Panel B. Nondiscretionary	10.76	−2.44	−0.19	8.13	−3.51	−4.62
Age 64 × post	(0.58)	(0.80)	(0.80)	(0.34)	(0.18)	(0.30)
	15.16	46.28	27.44	88.87	3.76	7.37
2011–2013 mean (age 64)	50,988					
Observations						
Panel C. ACS data						
Age 63–64 × post	6.5	0.18	−0.09	6.59	N/A	−6.59
	(0.29)	(0.53)	(0.46)	(0.32)		(0.32)
2011–2013 mean (age 63–64)	8.37	58.95	17.46	84.78		15.22
Observations	101,710					

Notes: This table presents regression results on changes in hospital payer shares using discharge data (panels A and B) and insurance coverage using ACS data (panel C) at the age 65 threshold using the RD-DD analysis. Coefficients presented are on the interaction of the indicator for being below age 65 and post-ACA period in equation (2a). Regressions were estimated on the sample of elderly patients, as described in Section III.A. We use bandwidths of one year in the discharge data and two years in the ACS sample. Larger bandwidth is necessary with the ACS sample since we do not observe age in months or days, only in years. The dependent variable is coverage by specific payer type. Miscellaneous includes Medicare, government employees, and workers' compensation. County coverage is not recorded in the ACS, and hence, self-pay is equal to uninsured. All models control linearly for age and include a full set of year fixed effects. Models using ACS data are weighted to make them representative of California population estimates. In models using the discharge data, standard errors are clustered by day-of-age cell. Online Appendix Table A.2 presents the full set of results using ACS data. These include a split of private coverage into employer-sponsored insurance and private nongroup, as well as robustness to different bandwidths and more flexible specification. Online Appendix Table A.4 presents corresponding robustness checks for the results using discharge data. Online Appendix Table B.2 presents results on payer mix at the age 21 threshold.

Table 2, columns 1–3 present results on changes in the shares of Medicaid, private, and miscellaneous payers, while columns 5 and 6 present corresponding results for self-pay and coverage through the county programs.

Table 2, panel A has two key implications. First, the share of insured among the elderly increased less than the increase in Medicaid (6 pp versus 8.7 pp). This is mainly due to a 2.6 pp decrease in the share of private payers.[22] Second, the decline in self-pay is only about 30 percent the size of the increase in Medicaid (2.6 pp versus 8.7 pp). In fact, there is a larger decline in the county indigent program (3.3 pp, or 35 percent of the Medicaid expansion) than in self-pay. The remaining 30 percent of the Medicaid expansion is offset by the decline in private insurance.

Estimates using the nondiscretionary sample in panel B corroborate these trends with minor variations—the decline in county represents a smaller share (33 percent)

[22] A concern here is whether the estimated decline in the share of private payers just reflects slower growth than Medicaid. However, we also find a decline in the number of stays covered by private insurers (−2.5 per 1,000 population) using this empirical approach.

of the Medicaid expansion relative to the decline in self-pay (43 percent). The decline in the share of privately insured patients is of similar magnitude as in the main estimates.

These results have two primary implications. First, Medicaid entirely drove the net increase in health insurance coverage among near-elderly hospital patients in California. The ACA exchange enrollments apparently did not lead to a net increase in the share with private insurance. In fact, even estimates using the ACS data (panel C) suggest no net change in private coverage.[23] Therefore, we interpret any effects on utilization and health as primarily occurring due to the Medicaid expansion.

Second, the near demise of local safety net programs implies that a substantial share of the Medicaid expansion—funded by federal taxpayers—replaced existing state and county spending on health care for the uninsured. We return to this issue in Section V and use these estimates together with results from the analysis on hospital finances to compute the size of this transfer.

C. *Utilization of Care*

Volume.—Since our data are conditional on discharge from a hospital, we cannot study the rate of hospital use at the individual level (for example, many individuals are not hospitalized during our study period). Instead, we use hospital stays or ER arrivals per 1,000 people per year (i.e., the utilization rate) as our preferred measure. We collapse the data to day-of-age-by-year-of-admission cells and normalize by estimates of California population for each age (64 years, 65 years, etc.) in each calendar year during our sample period, thus converting raw volume counts to utilization rates. We then estimate an exact analog of equation (2b). The coefficient of interest (θ_{22}) is accordingly interpreted as the estimated change in the discontinuity in the rate of utilizing hospital care post-ACA for the treated group relative to the comparison group.

Figure 3 presents the observed change in the post-ACA rate of utilization of hospital stays (panel A) and ER arrivals (panel B) for elderly patients by month of age. In addition, we plot fitted values obtained by estimating equation (2b). Panel A shows a decline in the rate of hospitalization for both 64- and 65-year-old patients, with a smaller decline for the treated group and a noticeable drop exactly at age 65. Panel B shows an increase in the rate of ER use for both groups, with a greater increase for 64-year-olds.

Table 3 presents the corresponding reduced form regression coefficients and IV estimates (interpreted as the change in utilization rate per percentage point increase in coverage). Panels A and B present estimates pertaining to hospital stays and ER arrivals, respectively. Table 3, panel A, column 1 presents results for all hospital stays. Columns 2 and 3 examine effects separately for hospital stays that originated

[23] The discharge data do not allow us to differentiate between exchange and nonexchange plans. It is possible that exchange plans did cause an increase in private insurance coverage. If true, this was apparently more than offset by a crowd out of other types of private coverage. Online Appendix Table A.2 provides more detailed results using the ACS data and shows that the increase in the share with private nongroup plans (the type that would be offered on the exchange) was offset by an equally large decline in the share with private employer-sponsored plans.

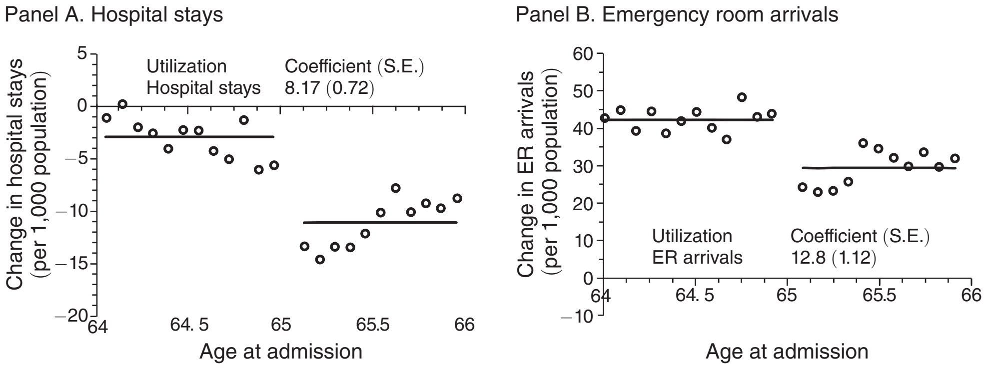

Figure 3. Utilization Rate (per 1,000 People per Year)

Notes: This figure presents the mean post-ACA change in number of hospital stays (panel A) and ER arrivals (panel B), i.e., including those patients who were eventually admitted as inpatients, per 1,000 California residents in each month-of-age cell. Raw discharges were converted to utilization rates using California population estimates obtained from the National Cancer Institute. The regressions were estimated on data at day-of-age–year level, but for presentation clarity, we collapse data to month-of-age level. Patients aged 64 constitute the treated group. We also plot corresponding fitted values (dashed lines) obtained by estimating equation (2b) on data collapsed to day-of-age–year cell, as described in Section IIIC. All models control linearly for age and include a full set of year fixed effects. We also note the estimated change in discontinuity, which is the coefficient on $d_i \cdot T_t$ in equation (2b). Standard errors are clustered by day-of-age cell.

through the ER and those that did not, since they may respond differently to changes in insurance coverage. Similarly, columns 4 and 5 present results separately for discretionary and nondiscretionary hospital stays. We find a differential increase among 64-year-olds of 6 percent of the mean (8 stays per 1,000 people per year), which eliminates 40 percent of the pre-ACA gap in hospital stays between 64- and 65-year-olds. The estimates indicate that much of the increase is driven by stays for elective or nonemergent reasons. For example, 95 percent of the increase is driven by more stays for discretionary conditions, and 60 percent by stays that did not originate in the ER.

Table 3, panel B, columns 1, 4, and 5 present corresponding results on ER use. The pattern of increase in ER use is similar to that of hospital stays, whether benchmarking it as a percentage of the mean level or against the pre-ACA gap between 64- and 65-year-olds. Across hospital stays and ER arrivals, the ACA resulted in an increase in the utilization rate that bridged about 35–40 percent of the pre-ACA gap in volume between 64- and 65-year-olds.[24]

The implied increase in hospital volume of 5–6 percent aligns well with the observed changes in utilization for nonelderly adults over this period. Online Appendix Figure A.2 presents the time series of hospital stays and ER arrivals (right axis) for patients aged 21–64. The figure plots raw discharges normalized by the estimated population in this age group by year, i.e., utilization rate per 1,000 individuals

[24] Our reduced form estimates are similar in magnitude to those reported by Card, Dobkin, and Maestas (2008). They examined the effects of the onset of Medicare coverage at age 65 on utilization of care and insurance coverage using data from California, Florida, and New York. They find an 8 percent increase in the rate of hospitalization at age 65, while we find a 6 percent increase post-ACA. They estimated increases of 5 percent and 14 percent in stays originating in the ER versus not, while our corresponding estimates are 3 percent and 10 percent, respectively.

Table 3—Patient Volume

Panel A. Hospital stays	All (1)	Through ER (2)	Not through ER (3)	Discretionary (4)	Nondisc. (5)
Age 64 × post	8.17	3.28	4.90	7.73	0.44
	(0.72)	(0.56)	(0.44)	(0.70)	(0.21)
IV estimate	1.37	0.55	0.82	1.30	0.07
	(0.12)	(0.10)	(0.08)	(0.12)	(0.04)
2011–2013 mean (age 64)	127	80	47	115	12
Observations	4,200				
Panel B. ER data					
Age 64 × post	12.80	N/A	N/A	12.17	0.63
	(1.12)			(1.07)	(0.29)
IV estimate	1.43			1.36	0.08
	(0.13)			(0.12)	(0.04)
2011–2013 mean (age 64)	287	207		266	21
Observations	4,200				

Notes: This table presents regression results on changes in volume of hospital care using the RD-DD analysis. Coefficients presented are on the interaction of the indicator for being aged 64 and post-ACA period in equation (2b). Regressions were estimated on the sample of elderly patients, as described in Section IIIC. The dependent variable is the rate of hospital stays or ER arrivals (i.e., including cases eventually admitted for inpatient care) per 1,000 people per year. To generate these utilization rates, we normalize raw discharges by population estimates for each age-year cell obtained from the National Cancer Institute. The IV estimates were obtained by scaling the reduced form coefficient by the increase in share insured (~6 pp) and should be interpreted as the change in utilization rate per 1 pp increase in share insured. Column 1 presents the results for all hospital stays. Columns 2 and 3 present results separately based on stays that originated through and not through ERs respectively. Columns 4 and 5 present results on stays for discretionary and nondiscretionary conditions, respectively. Nondiscretionary refers to about 15 conditions, such as heart attack, acute fractures and injuries, poisoning, etc., that are emergent and require immediate hospital care. Panel B, column 1 presents results for all ER arrivals, while columns 4 and 5 present corresponding results as in panel A. There are 700-day cells in each of 6 years and, hence, 4,200 observations in each regression. All models control linearly for age and include a full set of year fixed effects. Standard errors are clustered by day-of-age cell. Table B.2 presents results on utilization changes at the age 21 threshold.

per year. Consider the case of hospital stays—simply extrapolating the 2011–2013 values using a linear trend would predict about 50 stays per 1,000 people in 2016. The observed rate exceeds this prediction by about 3.5 stays per 1,000 people, or 6 percent of the mean rate over 2011–2013 (56.3). If we use the raw discharge volume changes instead, we obtain an observed increase of 5.5 percent. Similar analysis holds for the ER arrivals.

The IV estimates are also similar in magnitude across hospital stays and ER arrivals—a 1 percentage point increase in coverage leads to an increase in utilization of about 1.4 per 1,000 individuals. Since the baseline utilization rate of hospital stays is about 130 per 1,000, this implies a large increase in the use of hospital care—essentially a 100 percent increase for individuals gaining coverage. This is three times the estimate from the Oregon experiment (Finkelstein et al. 2012, Table 4). They report a LATE estimate of a 30 percent increase due to Medicaid coverage. In contrast, since the base rate of ER use is much greater (290 per 1,000 individuals), the corresponding implied increase in ER arrivals is about 50 percent, comparable to the 40 percent estimates reported by Anderson, Dobkin, and Gross (2012) for young adults and from the Oregon experiment (Taubman et al. 2014).

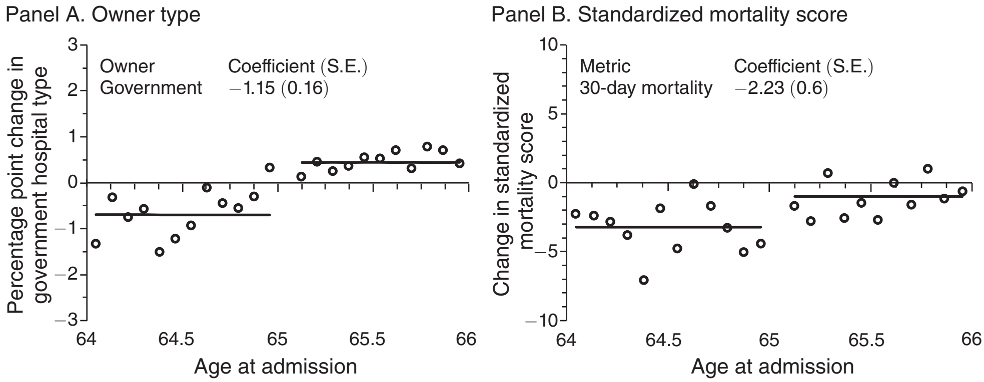

Figure 4. Hospital Choice: Owner Type and Quality

Notes: This figure presents the post-ACA percentage point change in the percent of hospital stays at government hospitals (panel A) and in mean standardized mortality score for patients, a variable with mean 0 and SD of 100 (panel B). We also plot fitted values obtained by estimating equation (2b) on case-level data, as described in Section IIIA. Patients aged 64 constitute the treated group. Regressions were estimated at the day-of-age–year level, but for presentation clarity, the data are collapsed to month-of-age level. Regressions control linearly for age and include year fixed effects. The estimated change in discontinuity, which is the coefficient on $d_i \cdot T_t$ in equation (2b), is also presented. Standard errors are clustered by day-of-age cell.

It is possible that the marginal individuals are sicker than existing Medicaid patients and, hence, need to consume more hospital care. Perhaps more importantly, our estimated increase may be driven by general equilibrium effects. Specifically, hospitals and physicians may have responded to the much-publicized Medicaid expansion and the increased reimbursement rate by expanding access and increasing treatment intensity for all low-income nonelderly patients, not only those acquiring Medicaid coverage (Alexander and Schnell 2020).

Choice of Hospital.—In addition to increasing hospital care, patients may also seek care at different hospitals after gaining formal insurance coverage, presumably to move to hospitals with more amenities or higher quality. We explore hospital choice on two dimensions—ownership type (e.g., public, private nonprofit, and private for-profit) and quality (as measured by risk-adjusted mortality and readmission scores).

Hospital Owner Type: Figure 4, panel A presents the change in the observed share of stays at government hospitals for elderly patients post-ACA. It also presents the corresponding fitted values obtained by estimating equation (2b) on case-level data. Figure 4, panel A indicates that patient volume shifted away from government-owned hospitals (~1.1 pp) post-ACA. The discontinuity in the share treated at government-owned hospitals is more diffuse than those in insurance coverage and volume, but the patterns for 64- and 65-year-olds are clearly different, with a larger reduction in government share among 64-year-olds.

Table 4, columns 1–3 present estimated effects on hospital share by owner type for elderly patients. Panel A presents results for all hospital stays. The estimates confirm the trends shown by the plot and suggest that for-profit hospitals gained

Table 4—Hospital Choice

	Owner type			Quality score	
	Nonprofit	For-profit	Govt.	Mortality	Readmission
	(1)	(2)	(3)	(4)	(5)
Panel A. All stays					
Age 64 × post	0.38	0.76	−1.15	−2.23	−0.94
	(0.24)	(0.19)	(0.16)	(0.60)	(0.55)
IV estimate	0.06	0.13	−0.19	−0.32	−0.14
	(0.04)	(0.03)	(0.03)	(0.09)	(0.08)
2011–2013 mean (age 64)	71.59	15.68	12.73	5.73	−2.88
Observations	558,220	558,220	558,220	470,165	471,561
Panel B. Nondiscretionary					
Age 64 × post	0.46	0.65	−1.11	−1.46	−1.82
	(0.79)	(0.62)	(0.57)	(1.89)	(1.82)
IV estimate	0.06	0.08	−0.14	−0.16	−0.20
	(0.10)	(0.08)	(0.07)	(0.20)	(0.20)
2011–2013 mean (age 64)	73.38	14.25	12.38	11.73	−7.04
Observations	50,988	50,988	50,988	43,336	43,672
Panel C. All ER arrivals					
Age 64 × post	1.43	0.67	−2.11	−1.12	−1.18
	(0.16)	(0.12)	(0.12)	(0.36)	(0.37)
IV estimate	0.16	0.07	−0.23	−0.11	−0.11
	(0.02)	(0.01)	(0.01)	(0.03)	(0.04)
2011–2013 mean (age 64)	69.74	12.90	17.37	16.42	−0.83
Observations	1,340,968	1,340,968	1,340,968	1,114,929	1,113,227

Notes: This table presents regression results on changes in hospital share using the RD-DD analysis. We explore changes on two dimensions—hospital owner type and quality scores. Coefficients presented are on the interaction of the indicator for being aged 64 and post-ACA period in equation (2b). Regressions were estimated on the sample of elderly patients, as described in Section IIIA. Panels A and B present results for the hospital stays and ER arrivals, respectively. The sample for hospital owner type contains ~560,000 discharges, while in the case of quality scores, the sample is smaller (~460,000) since some hospitals are not rated by CMS. The corresponding sample sizes in the case of ER arrivals are 1.3 million and 1.1 million, respectively. The dependent variables are indicators for nonprofit, for-profit, or government ownership (columns 1–3) and standardized 30-day mortality and readmission scores reported by CMS in 2009 (columns 4–5). All models control linearly for age and include year fixed effects. Standard errors are clustered by day-of-age cell. We also estimated a version of column 4 controlling for hospital ownership. Estimates were −1.5 (0.6) and −0.25 (0.36) for hospital stays and ER arrivals, respectively. Online Appendix Table B.2 presents results on hospital choice at the age 21 threshold.

about 70 percent of this shift in volume. Note that 64-year-olds were more likely to receive care at government-owned hospitals in the pre-ACA period. This shift from public to private hospitals among 64-year-olds after the ACA narrows the pre-ACA gap between 64- and 65-year-olds by 60 percent but does not eliminate it. The IV estimates imply a 20 percent decrease in the probability of receiving care at a public hospital upon gaining insurance coverage. These estimates remained unaffected when we included patient distance to hospital in the specifications, implying that this is not driven by proximity (e.g., an alternate interpretation could be that for-profit hospitals were advantageously located to benefit from the Medicaid expansion).[25]

[25] We used distance between the patient's and hospital's zip codes, obtained from NBER. Predictably, the coefficient on log distance is negative and highly statistically significant. The coefficient on public hospital remains

In fact, online Appendix Figure A.3 shows that public hospitals were more likely to be located in high-poverty-rate areas and, hence, enjoyed a location advantage over their privately owned counterparts. Note that while the share of public hospitals declines, we find that their patient volume remains stable in absolute terms since the ACA led to an increase in aggregate utilization.

Assuming that Medicare patients are unconstrained in their hospital choices, the lower share of government hospitals among 65-year-olds indicates patient preference for private hospitals. Hence, the most intuitive explanation for narrowing this gap post-ACA is that it is demand driven. However, we cannot rule out the possibility that private hospitals proactively courted ACA beneficiaries (such as exchange enrollees and Medicaid beneficiaries).[26]

To inform our interpretation, we replicated this analysis on the sample of nondiscretionary conditions (panel B) and ER arrivals (panel C). These patterns are more likely to reflect patient preferences since they are for emergencies and, hence, there is less scope for advertising or physician influence. The results using the nondiscretionary sample are strikingly similar to those in the main sample, albeit with larger standard errors. We also estimate a shift in volume of similar magnitude away from government-owned hospitals in the ER data, although nonprofit hospitals appear to be the main beneficiaries in this case. Taken together, these results suggest that the differential drop in the utilization of care in public hospitals among 64-year-olds largely reflects patient preference for privately owned hospitals.

Hospital Quality: Hospital ownership is correlated with quality or with perceived quality of care (for example, academic medical centers are generally high quality and nonprofit), but not perfectly so. To examine whether the above patient sorting is motivated by quality, we use two commonly accepted quality measures—risk-adjusted 30-day mortality and readmission rates—as indicators of hospital quality. We test whether patient volume shifted toward hospitals that were publicly certified by CMS in 2009 as having better-quality outcomes.

CMS calculates these measures for Medicare patients discharged from hospitals for a number of serious conditions. The raw mortality and readmission rates are adjusted for patient risk history and observed sickness at the time of admission.[27] We start with the risk-adjusted rates for hospitals, as reported by CMS in 2009, on three conditions: heart attack, heart failure, and pneumonia. We then compute the mean rate for each hospital and normalize it such that the distribution across hospitals is standard normal with a mean of 0 and standard deviation of 100.

Figure 4, panel B plots the observed mean normalized mortality scores and corresponding fitted values obtained by estimating equation (2b) on the y-axis against patient month of age on the x-axis. The plot is admittedly diffuse, without a clear

unchanged at -1.15 (0.16). The coefficient on for-profit hospital changes slightly to 0.73 (0.19).

[26] An alternate explanation could be that Medicaid managed care and exchange plans are more likely to exclude publicly owned hospitals in their networks. Prior evidence from California suggests that exchange plan networks are narrower but are not correlated with hospital ownership or quality (Haeder, Weimer, and Mukamel 2015). Thus, it seems unlikely that narrow networks are the primary reason for the shift in hospital shares.

[27] More details on the methodology are available at https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/OutcomeMeasures.html. The measures are available at https://data.medicare.gov/data/hospital-compare.

discontinuity at age 65. The fitted values indicate that the mean hospital mortality score increased for 65-year-old patients, while it held relatively constant for 64-year-olds, resulting in a relative improvement of about 2 pp. We do not present the corresponding plot for mean readmission scores since the estimated change is not statistically significant, although the point estimate is negative, implying that 64-year-old patients received care at relatively better-quality hospitals post-ACA.

Table 4, columns 4 and 5 present the formal estimated effects on mean hospital mortality and readmission scores, respectively. The coefficients are qualitatively and quantitatively similar across all three samples and indicate that patient volume among 64-year-olds has differentially shifted toward better-quality hospitals. In the pre-ACA period, 64-year-olds received care at lower-quality hospitals (0.04 standard deviation higher mortality rate) relative to 65-year-olds. The estimated effects for hospital stays indicate that the pre-ACA disparity between 64- and 65-year-olds decreased by about half. The IV estimates imply that gaining coverage is associated with receiving care at a hospital with 0.1–0.15 standard deviation better quality—a substantial change. As an additional test, we obtained alternative estimates where the specification controlled for hospital owner type. The coefficients drop in magnitude by about a third but remain statistically significant in the case of the mortality score, implying that patients sorted toward better-quality hospitals even *within* the same hospital owner type.

To convey the value of this shift in hospital quality, we use revealed preference estimates of the additional distance that patients are willing to travel to receive care at better hospitals. Tay (2003) examined Medicare data from California, Oregon, and Washington and estimated that heart attack patients were willing to travel up to eight miles farther to receive care at a hospital with a 3 percent lower mortality rate. Our results imply that 64-year-olds are now receiving care at hospitals with a 0.03 pp (2 percent of the standard deviation = 1.6 pp) lower mortality rate, or approximately 0.3 percent of the mean 30-day mortality rate for heart attack patients (~10 pp). Applying the estimate, this suggests that patients benefit by an amount equivalent to a 0.8-mile reduction in travel distance, or 12 percent of the median patient distance to hospital (7 miles) in the sample.

D. *Health Outcomes*

Small randomized controlled trials have detected no tangible benefits of insurance coverage on patient health (Manning et al. 1987; Finkelstein et al. 2012). Some quasi-experimental studies on the effects of Medicaid have found mortality benefits, albeit among children in most cases (Currie and Gruber 1996a; Bailey and Goodman-Bacon 2015; Goodman-Bacon 2018). The ACA was designed to explicitly extend insurance coverage for nonelderly adults—a group that has historically received less attention. In this section, we test the effects of the ACA on patient mortality, specifically in-hospital mortality, the largest component of 30-day mortality.[28]

[28] Due to data limitations, we do not observe 30-day mortality post-ACA. We obtained death-linked hospital discharge files over 2008–2011 from OSHPD to examine the link between in-hospital mortality and standard metrics of mortality. OSHPD creates these files by linking hospital discharge records with the state death

Online Appendix Table A.3, columns 1 and 2 present regression estimates on in-hospital mortality for elderly patients obtained by estimating equation (2b). Panels A and B present results for hospital stays and ER arrivals, respectively. Due to the increase in hospital use, there is a concern that an unobserved decrease in patient severity may lead to spuriously estimating a decrease in mortality. Focusing on the sample of nondiscretionary conditions helps mitigate this concern, and hence, we prefer to discuss these estimates (in column 2). The point estimate of the effect on in-hospital mortality is a large but statistically insignificant negative 0.55 pp, which is about 14 percent of the mean mortality rate for patients with these conditions. Prior to the ACA, 64-year-old patients had a higher in-hospital mortality rate than 65-year-old patients (by 0.12 pp), and this result suggests that they are now better off. The corresponding IV estimate implies that a 1 pp increase in coverage leads to an approximately 2 percent decline (coefficient of 0.068 relative to mean mortality rate 3.6) in in-hospital mortality for patients admitted with these urgent conditions.[29]

Although our mortality estimate is statistically insignificant, the magnitude of 0.07 pp compares well with results from two recent studies that examined the effects of gaining ACA mandated health coverage on subsequent mortality. Miller et al. (2021) use US census death data linked to the ACS to show that near-elderly adults (aged 55–64) in Medicaid expansion states experienced a 0.09 pp decline in 1-year mortality post-ACA relative to similar individuals in states that did not expand Medicaid. Goldin, Lurie, and McCubbin (2019) use evidence from a large field experiment to show that gaining insurance coverage leads to a robust decline of 0.17 pp in 2-year mortality for individuals aged 45–64.

A key argument used in favor of expanding insurance coverage was that greater immediate access to preventative care would circumvent later wasteful use of expensive ER/hospital care. Hence, a natural second outcome of interest is whether the ACA led to a decrease in avoidable use of hospital care. We followed Kolstad and Kowalski (2012)[30] to identify potentially avoidable episodes using the principal ICD-9 diagnosis codes. Online Appendix Table A.3, column 3 presents corresponding estimated effects on the share of stays and ER arrivals that were potentially avoidable. The coefficients are small and statistically insignificant, suggesting that there is no meaningful change. This is consistent with prior evidence from Tennessee showing that a contraction of Medicaid did not increase the share of uninsured stays for avoidable reasons (Ghosh and Simon 2015).

register. Hence, we can observe standard short-term mortality outcomes like 7-day and 30-day mortality through November 2011. We find that in-hospital deaths accounted for 79 percent and 64 percent of 7-day and 30-day mortality, respectively, for patients in these age groups. In-hospital death is also highly predictive of 30-day mortality across hospitals, with an R^2 of over 0.9.

[29] The IV coefficient on in-hospital mortality implies implausibly large effects for those gaining insurance coverage. However, this may be an example of a violation of the exclusion restriction. The Medicaid expansion may have led to widespread improvements in quality of care for noncomplier patients as well, i.e., 64-year-olds who previously had insurance coverage. This is another example of potential general equilibrium effects due to the ACA.

[30] Potentially avoidable care hospitalization is defined only for hospital care where the primary diagnosis code pertains to a condition of the endocrine, nervous, circulatory, respiratory, digestive, or ill-defined system. These categories account for about 55 percent of the total sample of elderly patients in 2011–2016.

E. *Robustness and Falsification Checks*

Alternate Specification.—Our preferred specification allows the slope with respect to age to differ for 64- and 65-year-old patients but constrains the slopes to remain unchanged in the postperiod. In this subsection, we test robustness to relaxing this restriction. Online Appendix Table A.4 presents corresponding results on all key outcomes—changes in insurance coverage (panels A and B, columns 1–6), utilization (panels C and D, columns 1–2), hospital choice (panels C and D, columns 3–5), and patient health (panels C and D, column 6). To facilitate comparison, the first row in each panel repeats the main coefficients. Panel A2 presents results on changes in payer shares using the more flexible specification, holding the bandwidth at 1 year around the benchmark age of 65. Panel B2 presents corresponding results using a two-year bandwidth.

The results exhibit qualitatively similar patterns, and most have only minor differences in point estimates. The key exception is a small and statistically insignificant coefficient for the effect on the use of public hospitals in column (3) of panel C2. However, this is an outlier across our robustness tests, with the other estimates for this outcome falling in a narrow range around -1. Overall, making the specification more flexible tends to recover larger coefficients.

Alternate Bandwidth.—We prefer one year as the narrowest feasible bandwidth to implement the RD-DD design. However, we test robustness to other choices by replicating results using a larger bandwidth of two years instead. Table A.4, panel B1 presents corresponding results when we expand bandwidth, while panel B2 presents coefficients obtained using a larger bandwidth and more flexible specification. These results are very similar to the main estimates.

Falsification.—A valid identification concern is that the results may be partially or fully driven by preexisting economic trends that may differentially affect 64-year-old patients (e.g., the decline in private coverage was initiated by the recession). To investigate this possibility, we replicated the above analysis over the period 2008–2011, before the ACA insurance expansions were implemented. Ideally, if the pre-ACA coefficient (2011–2013) estimates a stable discontinuity in coverage, then we should find similar estimates in the 2008–2009 period as well, i.e., $\theta^{08-11}_{\cdot,1} = \theta^{11-16}_{\cdot,1}$. If the post-ACA coefficient captures changes only due to the ACA, then we would find a zero (or very small) effect in the placebo analysis, i.e., $\theta^{08-11}_{\cdot,2} \approx 0$.

Table 5 presents results from this placebo analysis on insurance coverage, utilization, hospital choice, and patient health for hospital stays. It summarizes effects on key outcomes from Tables 2, 3, and 4. The top row in each panel presents the estimated difference between 64- and 65-year-olds over 2008–2009, $\theta^{08-11}_{\cdot,1}$ from equation (2a)/(2b), while the second row in each panel presents the change in this gap post-2010, $\theta^{08-11}_{\cdot,2}$. The coefficients for post-2010 changes typically are not significantly different from zero or are small in magnitude. Overall, the pattern of results does not mimic the post-ACA results. For example, we find an increase in self-pay and no change in the rate of hospitalizations or the share of

Table 5—Falsification Exercise

Panel A. Payer shares	Medicaid (1)	Private (2)	Miscellaneous (3)	Insured (4)	County (5)	Self-pay (6)
Age 64	9.78	25.58	−41.09	−5.73	2.44	3.29
	(0.29)	(0.39)	(0.39)	(0.17)	(0.09)	(0.13)
Age 64 × post	0.70	−0.75	−0.49	−0.55	0.20	0.35
	(0.23)	(0.31)	(0.31)	(0.14)	(0.08)	(0.11)
2008–2009 mean (age 64)	18.13	47.18	27.82	93.13	2.77	4.10
Observations	336,084					
Panel B. Utilization	Stays	ER arrivals		Govt.	For-profit	RA mort.
Age 64	−20.06	−31.81		1.73	−0.78	1.01
	(1.34)	(1.69)		(0.27)	(0.31)	(0.87)
Age 64 × post	−0.53	0.45		0.22	0.19	1.24
	(1.15)	(1.62)		(0.22)	(0.25)	(0.75)
2008–2009 mean (age 64)	141	270		12.31	15.23	3.97
Observations	2,800			336,084	336,084	283,965
Panel C. Health	Mortality	Mort (ND)				
Age 64	0.05	−0.45				
	(0.13)	(0.51)				
Age 64 × post	0.18	0.59				
	(0.11)	(0.42)				
2008–2009 mean (age 64)	2.84	3.76				
Observations	336,084	29,193				

Notes: This table presents results of a falsification exercise for the RD-DD analysis using data from 2008 to 2011 (pre-ACA) imagining a placebo ACA implementation in 2010. Coefficients presented are on the interaction of the indicator for being aged 64 and post-2010 in equations (2a) and (2b). This exercise provides equivalent estimates to the main estimates on insurance coverage (Table 2), utilization (Table 3), hospital choice (Table 4), and health (online Appendix Table A.3). All models control linearly for age and include year fixed effects. When examining effects on volume, we collapse the data to the day-of-age–year level. When examining effects on patient health, models control for patient gender and condition category. Mort (ND) refers to in-hospital mortality in the sample of nondiscretionary cases. Standard errors are clustered by day-of-age cell.

admissions at government hospitals. There is a small increase in the Medicaid share of 0.75 pp and a decrease in private coverage of similar magnitude, which may be due to the "early" Medicaid expansion implemented in California in 2011 (Golberstein, Gonzales, and Sommers 2015; Sommers et al. 2015; Wherry and Miller 2016). Nevertheless, these coefficients are small relative to the effects obtained after the full expansion took effect in January 2014.

Age 21 Threshold.—As discussed in Section IC, Medicaid eligibility also changed discontinuously at age 21 in California in the pre-ACA period. Although the ACS does not suggest a sharp change in Medicaid coverage at age 21, there is a large and sharp discontinuity in the hospital discharge data. We replicated the RD-DD analysis on the sample of patients aged 20–21 and estimated effects on the same outcomes. The patterns for young patients are qualitatively consistent with those found for the elderly, and in some cases, the effects are similar in magnitude as well.

For example, there is a large increase in the share of Medicaid, and about half of the increase is offset by a decline in the county indigent program. Similarly, there is a modest increase in rate of hospital and ER use, and patients are more likely to receive care at privately owned hospitals post-ACA. Online Appendix B presents the results and provides a fuller description.

Extending to All Nonelderly Adults.—The RD-DD estimates are weighted toward the experience of near-elderly individuals (Lee and Lemieux 2010). However, patients aged 64–65 represent less than 10 percent of the nonelderly adult (21–64) patients in our sample and experienced a smaller increase in coverage than did other age groups (Figure 1).

We tested robustness to extending the sample to all nonelderly adults using an alternative research design that exploits pre-ACA variation in poverty rates across hospital markets. Our thought experiment is that markets with greater poverty rates pre-ACA experienced a greater "insurance expansion shock" than markets with lower poverty. We briefly describe the key results here, leaving details for online Appendix C.

The results from this exercise (see online Appendix Table C.1) align well with the RD estimates on changes in the shares of different payers. The key deviation is that we find no net crowd out of private payers.[31] The estimated effects on utilization are also similar to those implied by the RD estimates. They also imply sorting of patients away from public hospitals, although the primary beneficiaries appear to be nonprofit hospitals. In fact, nonprofits gain market share at the expense of both public and for-profit hospitals, a pattern that we also find when we examine hospital finances. The coefficients on patient sorting are not statistically significant, implying that these patterns may be sharper for patients aged 64 than in the full sample.

IV. Effects on Hospitals

This section has two goals. First, we leverage detailed data on hospital finances to quantify the impact of the ACA on hospital revenue and operating margins, including heterogeneity in these effects across hospitals by owner type. We then quantify how the influx of public funds affected hospital choice of inputs (labor, capital) and capacity expansion. Loosely speaking, the first exercise answers the question, "How much incremental money did the ACA generate for hospitals?" and the second exercise answers, "What did hospitals do with this money?"

A. *Empirical Strategy*

We implement a differences-in-difference research design that uses cross-sectional variation across hospitals in the pre-ACA share of nonelderly adult

[31] If we limit the sample to ages 60–64, we do get a negative (insignificant) point estimate on the share of private payers. It is possible that crowd out was greater among 64-year-olds than among all 21–64-year-olds since their average health care costs are much greater, and so there would be more for employers (and possibly employees if savings are passed on through wages) to gain from dropping coverage for this group than for younger individuals.

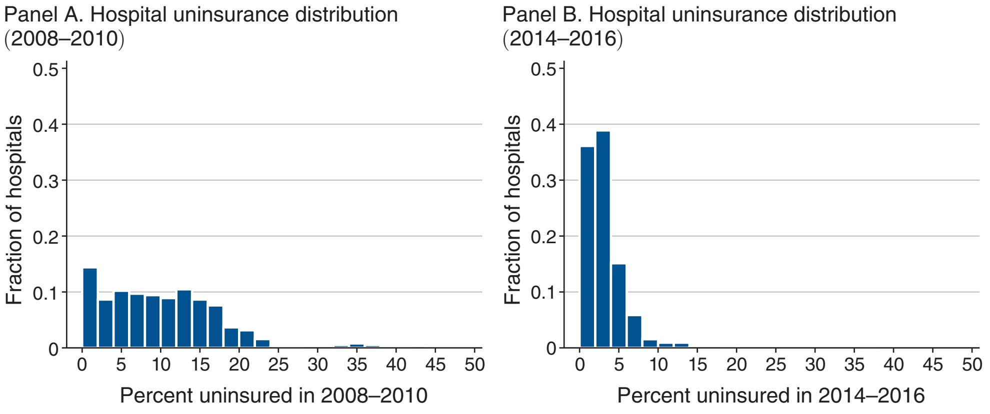

Figure 5. Hospital Uninsurance Distribution

Notes: This figure presents histograms (by hospital) of the percentage of patients that did not have insurance coverage in 2008–2010 (panel A, pre-ACA) and 2014–2016 (panel B, post-ACA), respectively. Uninsured patients are those coded as self-pay or county indigent. These histograms were computed using the discharge data on hospital stays and make use of the same sample restrictions as in our main analysis—limit to nonelderly adults (aged 21–64) in general acute care hospitals, exclude childbirth related cases, and exclude cases for individuals with zip codes missing or located outside of California. The percent uninsured is top coded at 50 percent (one hospital in 2008–2010). We use this variation in uninsurance across hospitals to identify effects of the ACA on hospital finances.

patients who were uninsured. The thought experiment is that hospitals located in low-income markets served a higher share of uninsured patients in the pre-ACA period and experienced a greater insurance "shock" relative to hospitals located in more affluent markets. Figure 5 illustrates the magnitude of this variation across hospitals before and after the ACA. Panel A presents a histogram of hospital uninsurance pre-ACA, 2008–2010, calculated using hospital discharge data. The uninsurance rate is calculated as the fraction of discharges that were self-pay or covered by county indigent programs from 2008 to 2010. Most hospitals ranged from 0 percent to approximately 30 percent, with mean uninsurance of 14 percent. Hospitals in the top quintile had about a 20 percentage points greater baseline uninsurance share than hospitals in the bottom quintile. Panel B presents the distribution after the implementation of the ACA, 2014–2016. The range noticeably shrank, with most hospitals falling below 15 percent.

Equation (3a) presents the estimating equation for this approach. For this exercise, we deploy data at the hospital-year level on revenue, profitability, utilization, and factor inputs over the period 2011 to 2016. To mitigate the influence of small facilities, we weight each hospital by the total number of nonelderly adult discharges over 2008–2010:

$$Y_{ht} = \alpha_h + \gamma_t + \chi \cdot Uninsured_{h-0810} \cdot T_t + \epsilon_{ht}. \tag{3a}$$

The key identification assumption with this approach is the absence of differential trends across hospitals at different levels of baseline patient uninsurance levels. In order to test for the presence of pretrends, we also estimate the flexible dynamic specification (3b), in which we interact our key explanatory variable with several distinct year indicator variables:

$$(3b) \qquad Y_{ht} = \alpha_h + \gamma_t + \sum_{\substack{s=2011 \\ \neq 2013}}^{2016} \chi_s \cdot \mathit{Uninsured}_{h-0810} \cdot I(t = s) + \epsilon_{ht}.$$

B. *Hospital Revenue and Profitability*

Table 6, panel A presents estimated coefficients on revenue, expressed in thousands of dollars per bed. We present effects on total revenue as well as on three components (Medicaid including managed care, private, and all others). Column 5 presents the effects on the total of Medicaid, self-pay, and county payers, which we call "net Medicaid."[32] This variable helps quantify the increase in Medicaid after netting out decreases in these two payers. All revenue variables are deflated to be in 2016 dollars (in thousands) using the CPI-U and normalized by the hospital's average number of licensed beds in the baseline period.[33]

The key takeaway on hospital revenue is the large differential increase in Medicaid revenue for hospitals with a higher baseline share of uninsured patients. The average hospital received an additional \$71,000 (\$508,000 $\times$ 0.14, the mean uninsurance rate) in annual Medicaid revenue per bed. This estimate implies an incremental \$5.4 billion of Medicaid spending on hospital care each year over 2014 to 2016.[34] According to the financials data, Medicaid hospital spending was about \$17 billion per year over 2011–2013; hence, our estimate implies a 30 percent increase in Medicaid hospital spending. An alternative benchmark is to compare our estimate to the observed increase in Medicaid hospital spending over this period of about \$6.6 billion per year. Hence, our results imply that 80 percent of the observed increase in spending over this period was due to the ACA expansion.

The estimated effect on total revenue for the average hospital is similar in magnitude (\$471,000 $\times$ 0.14 $\approx$ \$66,000 per bed), with the increase in Medicaid offset by the loss of revenue from the counties and self-paying patients. However, since total revenue was about five times as large as Medicaid alone, this is a much smaller percentage increase. Figure 6, panel A presents event study plots obtained by estimating equation (3b). The annual estimates are consistent with the average point estimates discussed above. Hospitals with greater baseline uninsurance appear to have a decreasing trend of Medicaid revenue in the pre-ACA period, but the trend

[32] OSHPD separately reports revenue from self-pay patients under the category "other payers."

[33] To account for outliers in the financial data, we winsorize the top 1 percent of revenues, volume measures (stays and visits), and expansion variables (capital expenditures and license beds). For operating margin, we also winsorize outliers in the bottom 1 percent of values since some hospitals reported extremely negative margins. We winsorize by year, hospital type (government and privately owned), and, when applicable, payer type (e.g., Medicaid, private, etc.) and type of service (inpatient versus outpatient). We compute total revenue as the sum of the winsorized components rather than winsorizing it independently so that the coefficients add up across columns. Furthermore, by winsorizing values by hospital type, we eliminate the possibility that outliers of one hospital type drive our results in panel B.

[34] We obtain \$5.4 billion using the following calculation: multiply the \$71,000 per bed increase with the mean number of beds per hospital, 235 = \$16.7 million per hospital, into 320 general acute care hospitals in the sample = \$5.4 billion.

Table 6—Hospital Finances

Panel A. Revenue	Total rev. per bed ('000$) (1)	Medicaid per bed ('000$) (2)	Private per bed ('000$) (3)	All other per bed ('000$) (4)	Net Medicaid per bed ('000$) (5)
Uninsured × post	471.3	508.3	39.9	−77.0	317.7
	(198.0)	(147.8)	(89.1)	(104.8)	(174.1)
Observations	1,923	1,923	1,923	1,923	1,923
Dependent variable mean (2011–2013)	968	192	411	365	229
Panel B. Components	Volume		Profitability		
	Inpatient discharges per bed	Outpatient visits per bed	Mean IP rev. per discharge ('000$)	Mean OP rev. per visit ('000$)	Op. margin per bed ('000$)
Uninsured × post	−5.8	−58.2	10.0	0.07	326.0
	(3.6)	(132.8)	(3.4)	(0.2)	(133.2)
Observations	1,923	1,923	1,923	1,845	1,923
Dependent variable mean (2011–2013)	36	645	18.7	0.8	39

Notes: This table presents regression results examining effects on hospital finances by exploiting baseline (2008–2010) variation in hospitals' uninsured patient shares, as discussed in Section IV.A. Coefficients presented are for the interaction of baseline uninsurance and an indicator for the post-ACA period in equation (3a). Panels A and B present estimated effects on revenue and components of revenue (namely, volume and prices), respectively. All revenue variables are expressed in thousands of dollars deflated to 2016 using the CPI-U. "Net Medicaid" refers to the sum of Medicaid, county, and self-pay revenue. We winsorize values for revenue and volume at the ninety-ninth percentile and for operating margin at the first and ninety-ninth percentile (more details in footnote 33). Operating margin is reported by hospitals to California as a percentage and is calculated as the ratio of the difference between operating revenue and costs over operating revenue. The bottom rows present the number of observations (about 320 hospitals × 6 years) and mean value of each dependent variable pre-ACA, i.e., 2011–2013. 78 hospitals have no outpatient visits or revenue and, hence, drop out when examining mean revenue per outpatient visit. All models include a full set of hospital and year fixed effects. Hospital observations are weighted by their number of discharges in 2008–2010. Standard errors are clustered by hospital. The weighted mean baseline share of uninsured patients across hospitals was 0.14.

reverses sharply after 2013. This suggests that our point estimates may understate the magnitude of the increase in Medicaid revenue due to the ACA.

Since the Medicaid expansion was accompanied by a decline in county programs and self-pay, perhaps a more realistic measure of the increase in hospital revenue is one that accounts for this decline. Column 5 presents the effect on Medicaid incorporating these two payers. The coefficient is significant at the 10 percent level and implies an increase of $45,000 per bed for the average hospital ($318,000 × 0.14), or $3.4 billion in aggregate, following the same approach as above.

Table 6, panel B examines effects on volume and average reimbursement components to help explain their role in the revenue effects reported above. The nature of the data makes it necessary to examine quantity and price separately by inpatient and outpatient services. Note that the volumes reported in the financial data cover patients across all ages and cannot be disaggregated by age. Examining reimbursements and volume separately helps clarify that the aggregate increase in revenue is driven entirely by the former, consistent with Medicaid replacing lower-paying self-pay or safety net payers. A hospital with 10 percentage point higher share uninsured at baseline received $1,000 more per inpatient stay post-ACA (panel B, column 3). In contrast, hospitals with greater baseline uninsurance lost patient

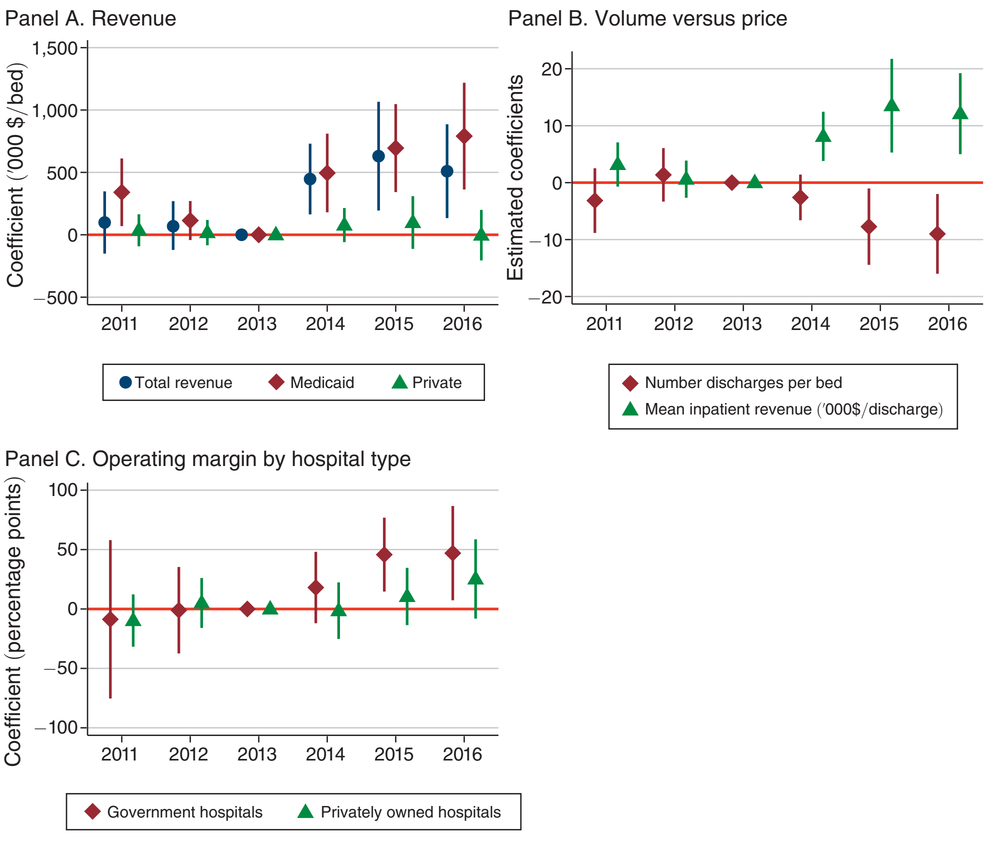

Figure 6. Effects on Hospital Finances

Notes: This figure presents event study results using hospital-year financial data from OSHPD. We plot coefficients on the interaction of $Uninsured_{h-0810}$ with indicators for each year s from 2011 to 2016, omitting 2013 as the reference year, obtained by estimating equation (3b) with various outcome variables. Bars indicate confidence intervals at the 95 percent level. $Uninsured_{h-0810}$ is the share of hospital h patients coded self-pay or county indigent over 2008–2010. In panel A, the revenue values have been deflated to be in thousands of 2016 dollars. Panel B presents patterns for number of inpatient stays per bed (volume) and mean revenue per discharge in thousands of 2016 dollars (price). Panel C presents results on operating margin obtained by estimating models separately on the sample of government and private hospitals. Prices here refer to mean reimbursement per hospital stay. All models include hospital and year fixed effects. Hospital observations are weighted by their number of discharges in 2008–2010.

volume relative to those previously serving a lower share of uninsured patients, though the point estimates in panel B, columns 1 and 2 are not precisely estimated. Figure 6, panel B presents event study plots illustrating the contrast in patterns for price and volume. Reassuringly, there is no evidence of differential trends prior to the expansion.

Since private hospitals served a lower proportion of uninsured patients than their publicly owned counterparts (11 versus 29 pp), these results corroborate our findings in Section IIIC on patient reallocation from public toward privately owned hospitals. The coefficient of −5.8 in panel B, column 1 implies that the average public hospital experienced a decrease of 1.1 stays per bed (-5.8×0.18) relative to the average privately owned hospital, about 4 percent of the pre-ACA mean volume at public hospitals (1.1/28).

Driven by the increased average reimbursement per stay and limited changes in volume, hospitals with greater baseline uninsurance experienced greater profitability. Panel B, column 5 presents the results on total reported operating surplus per bed, computed as the difference between operating revenue and costs.[35] The average hospital gained about \$46,000 per bed in operating surplus (\$326,000 $\times$ 0.14), or an aggregate increase of \$3.4 billion in reported hospital surplus each year due to the ACA. Note that this is nearly identical to the increase in Medicaid spending, net of the decline in self-pay and county.

Public hospitals served a much greater proportion of uninsured patients prior to the ACA. Hence, they experienced a greater insurance "shock" than privately owned hospitals, and we hypothesize a differentially greater impact on revenue, mean reimbursements, and profitability. We tested for heterogeneity in effects by hospital owner type using a standard triple difference specification with nonprofit hospitals as the reference group and explored whether there were differential effects for public and for-profit hospitals. Online Appendix Table A.6 presents the corresponding results. To facilitate comparison with the main results, panel A reproduces the coefficients reported in Table 6.

The coefficients in this exercise are more noisily estimated, and differences across hospital types are rarely statistically significant. Hence, we focus on overall patterns rather than specific coefficients. There are two key takeaways. First, the average effects discussed above mask a stark contrast between effects for nonprofits and for-profits. For example, nonprofits experienced an increase in both volume and mean reimbursement, resulting in a large increase in revenue relative to that for the average hospital (coefficient of 1,024 versus 471 discussed above). For-profits appear to have lost on both aspects, resulting in a differential decline in total revenue.[36] Second, as hypothesized, public hospitals gained the most in mean reimbursement per discharge and in operating margin, although the differences relative to nonprofits are not statistically significant. Public hospitals reported a negative mean operating margin of about \$66,000 per bed pre-ACA. The coefficients in panels C and D, column 5 imply that public hospital profitability increased substantially. Assuming that California taxpayers would have otherwise continued to fund these deficits, this represents another transfer from federal to state and local taxpayers.[37]

[35] Operating revenue is largely composed of patient revenue (90+ percent) but also includes nonpatient revenue due to food and merchandise sales. It does not include investment income. Operating cost is opaque since we do not observe its components.

[36] The RD-DD analysis of 64–65-year-old patients implies that for-profits increased their share of patients. However, these results do not hold when we study the sample of all nonelderly adults (ages 21–64). Instead, the geographic analysis in online Appendix C suggests that nonprofit hospitals gained share. Intuitively, results on hospital finances are consistent with effects estimated on the entire nonelderly adult sample.

[37] Previous studies have argued that public hospitals operate under soft budget constraints (Duggan 2000; Baicker and Staiger 2005) and, hence, the increased revenue due to Medicaid would be offset by an equivalent reduction in public subsidies. Our results appear to contradict these findings; however, future reductions in DSH payments may mitigate the revenue gains for public hospitals.

C. *Hospital Input Choices*

We also investigate how hospitals deployed the incremental public funds. Online Appendix Table A.5 presents estimated effects on various measures of labor and capital inputs. Panel A, columns 1–7 present effects on payroll, part-time and full-time staff, physicians and nurses, and mean salary, all similarly scaled by the number of beds. The results suggest no meaningful changes on any measure of labor input except an average decline in salary of \$3,700 per full-time equivalent (FTE) (column 7, \$26,500 $\times$ 0.14). While this implies that hospitals with greater baseline uninsurance differentially paid lower salaries post-ACA (or changed the composition of their workforce), we interpret this result with caution since we find differentially declining pretrends in payroll per bed and per FTE. Panel B, columns 1–3 indicate no effects on assets, capital spending, or bed capacity.

The results on revenue, input choices, and profitability collectively imply that the incremental revenue did not substantially affect hospital input decisions, and the additional money largely added to hospital surplus. We interpret these findings as reflecting short-term responses in an environment of uncertainty over the future of the ACA.

V. A Decomposition of Incremental Medicaid Spending

We combine our results on hospital utilization and finances, and we decompose the estimated incremental annual Medicaid spending of \$5.4 billion into four objects of policy interest. First, we quantify the spending on net incremental hospital care. Second, we quantify the reduction in payments to hospitals by self-pay individuals—a primary goal of the ACA. Third, we quantify the transfer from federal taxpayers to hospitals due to the increase in reimbursement rates when Medicaid covered lower-paying self-pay and county-sponsored patients. Fourth, we quantify the transfer from federal taxpayers to state and local taxpayers in California. This occurs through two channels—financing hospital care for erstwhile county indigent patients and reducing the subsidy for public hospitals. Table 7 summarizes these calculations.

We make two key assumptions to simplify this analysis. First, we assume that there was no net change in the share of privately insured patients in California hospitals due to the ACA. This follows from the results on payer mix in Section III, where we found small and inconsistent effects on private coverage. This is also consistent with results using the ACS data. Second, we assume that changes in patient volume shares lead to equivalent changes in spending. This assumption rules out the possibility that patients experience a change in hospital care intensity if they are covered by Medicaid versus being self-pay or county indigent. This is, admittedly, a strong assumption, since hospitals may treat Medicaid patients more intensely versus if they were uninsured (Doyle 2005). However, we find evidence consistent with this assumption. For example, when we examine effects on hospital charges (which often proxy for treatment costs), we find negligible effects post-ACA at hospitals that experienced a greater increase in the share of insured patients.[38]

[38] Specifically, we assume that self-pay and county patients are relabeled as Medicaid but receive the same intensity of care as before. Any increase in mean reimbursement is then attributed as the difference in reimbursement

TABLE 7—MEDICAID HOSPITAL SPENDING DECOMPOSITION

Item	Value ($ bn.)
Δ Medicaid spend	5.4
1. Δ Volume	
Net increase in volume (percent)	22
Value	1.2
2. Δ County program	
Proportion replaced (percent)	37
Value	2.0
a. County spend	0.9
b. Δ Reimbursement	1.1
3. Δ Self-pay	
Proportion replaced (percent)	41
Value	2.2
a. Patient spend	0.8
b. Δ Reimbursement	1.4
4. Δ to hospitals (2b + 3b)	2.5
a. To public hospitals	1.1
b. To private hospitals	1.4
5. Δ to taxpayers (2a + 4a)	2.0

Notes: This table summarizes calculations to decompose total incremental spending on hospital care (including outpatient care) by Medicaid into different components. See Section V for a detailed description. We rely on observed reimbursements by different payers, estimated effects on hospital finances, and changes in hospital utilization for different payers using the nonelderly patient sample (online Appendix Table C.1) to arrive at these estimates. Row 1 computes the share due to increase in Medicaid hospital stays, net of declines in stays covered by other payers. Rows 2 and 3 allocate the remaining amount toward replacing spending by self-pay patients and county programs. We split these amounts into two parts—the replacement value using rates offered by these programs pre-ACA and the residual that is due to greater reimbursement rates offered by Medicaid. Row 4 presents the total incremental revenue for hospitals due to the increase in reimbursement and then decomposes this amount into the portions sent to public versus private hospitals. To obtain this decomposition, we used the triple difference coefficients obtained on the sum of Medicaid, county, and self-pay revenue (online Appendix Table A.6, panel B, column 5). The transfer to California taxpayers is the sum of avoided county program spending (row 2a) and greater reimbursements to publicly owned hospitals (row 4a). All values are in billions of 2016 dollars or in percent.

These two assumptions allow us to interpret the increase in aggregate volume as the net increase in Medicaid volume, adjusting for declines in county and self-pay. Further, we can allocate an equivalent share of the estimated total increase in Medicaid spending toward incremental utilization. Using changes in volume, we can also allocate the share of Medicaid spending that replaced other payers. For this exercise, we use estimated effects on hospital volume obtained using the entire nonelderly adult sample (see online Appendix Table C.1), since they are more likely than the RD-DD estimates to be representative of the effects on aggregate hospital finances reported in the previous section.

rates between Medicaid and these payers and, therefore, is a transfer to hospitals. When we examine effects on log hospital charges, we obtain a coefficient of 0.08 with a standard error of 0.11, implying a statistically insignificant average effect of $0.08 \times 0.14 = 0.01$.

Online Appendix Table C.1, panel B implies that the net increase in total volume was about 22 percent the size of the estimated increase in Medicaid volume (coefficient of 785 in column 1 versus 3,529 in column 2). Accordingly, we allocate an equivalent share of incremental Medicaid spending (22 percent of 5.4 $\approx$ \$1.2 billion) due to greater hospital volume in Table 7, row 1. This amount could be interpreted as providing greater risk insurance for patients since it funded incremental hospital care. However, given that much of the increase in hospital volume was for discretionary conditions, some of this could also be driven by moral hazard or low-value care induced by providers.

Having accounted for spending on incremental utilization, the remainder (approximately \$4.2 of \$5.4 billion) covered patient volume previously covered by self-pay and county programs. We quantify the components that replaced spending by county programs and self-pay patients based on their relative declines as estimated in the geographic analysis.[39] We apply these percentages to obtain the corresponding values reported in rows 2 (\$2.0 billion) and 3 (\$2.2 billion) of Table 7. We observe large differences in mean reimbursement per hospital discharge across these payers prior to the ACA—the values for county programs and self-pay patients were, respectively, about 45 percent and 35 percent as large as the mean Medicaid reimbursement.[40] We use these observed ratios to split the replacement values discussed above into two components—the portion that these payers would have spent assuming their lower reimbursements and the remaining "windfall" for hospitals since they effectively received a price increase for their services. We estimate that Medicaid substituted about \$0.9 billion (45 percent of \$2 billion) of hospital spending by counties (row 2a) and another \$0.8 billion (35 percent of \$2.2 billion) previously incurred by self-pay patients (row 3a). The remaining amounts (\$1.1 and \$1.4 billion, respectively) were effectively transfers from federal taxpayers to hospitals through higher reimbursement rates (rows 2b and 3b). The total transfer to hospitals due to higher reimbursements is presented in Table 7, row 4 (\$2.5 billion).

We then allocate the share of \$2.5 billion received by public hospitals. Using the triple difference coefficients discussed in the previous section (see online Appendix Table A.6B, column 5), we quantify that about 40 percent of the net revenue gain (\$1.1 billion) went to public hospitals, which is the value reported in Table 7, row 3a.[41] Hence, privately owned hospitals received \$1.4 billion, or about 25 percent of incremental Medicaid spending. We can then compute the total transfer to California taxpayers as the sum of higher Medicaid reimbursement rates (\$1.1 billion) and avoided county indigent spending (\$0.9 billion), reported in Table 7, row 5.

[39] Of the total decline in volume across self-pay and county programs reported in Table C.1, panel B, self-pay accounted for 52 percent $(1{,}305/[1{,}195 + 1{,}305])$. We scale these appropriately so that they add to 78 percent, as the remaining 22 percent accounts for greater volume.

[40] County and self-pay programs reimbursed hospitals for inpatient care at about 45 percent (\$7,000) and 35 percent (\$5,300) of the level of Medicaid (\$15,400), respectively, over the period 2011–2013. The gaps were slightly larger in the case of hospital outpatient care. We used the ratios determined by inpatient care since it accounts for a large fraction of spending.

[41] We compute the share of public hospitals as follows. The coefficient corresponding to public hospitals in online Appendix Table A.6B on Medicaid, including county and self-pay (column 5), is $366 + 47 = 413$. The aggregate increase across all public hospitals is 413×0.29 (mean uninsured share for public hospitals) $\times$ 208 (mean number of beds) $\times$ 58 public hospitals = \$1.4 billion, which is 43 percent of the \$3.4 billion increase across all hospitals.

To summarize, this exercise implies that about 60–65 percent of incremental Medicaid hospital spending due to the ACA either replaced existing spending by California taxpayers ($2 billion, ~37 percent) or provided transfers to privately owned hospitals via higher reimbursement rates ($1.4 billion, ~25 percent). The remaining 35–40 percent financed hospital care for self-pay patients or enabled care that would not have occurred otherwise.

Combining the findings from the decomposition analysis with the effects on aggregate hospital finances, we also estimate the increase in hospital revenue per change in uninsured rates due to the price effect of expanding coverage. This helps inform the policy debate over the incidence of uninsurance cost on hospitals. Our regression estimates imply an increase of $9,300 in inpatient revenue and $230 in outpatient revenue per avoided uninsured stay and visit, respectively. Applying the utilization rate of hospital stays and outpatient visits observed in the NHIS, we translate these estimates to an aggregate increase of $790 in hospital revenue per change in uninsured rates in the population. Reassuringly, this is very similar to the estimate obtained by Garthwaite et al. (2018) using entirely different data and policy experiments.[42]

VI. Conclusion

In this paper, we estimate the effects of the ACA's public insurance expansions through the lens of California's hospital sector using the universe of all hospital stays and ER visits as well as data on hospital finances over 2008–2016. We find that the Medicaid expansion reduced the share of self-pay patients as well as those covered by county-run safety net programs. Hospital and ER utilization increased modestly, albeit large in magnitude relative to the change in insurance coverage. The increase in hospital stays is about three times what we would predict based on partial equilibrium insurance experiments, suggesting that general equilibrium effects are large. We speculate that supply-side responses are responsible, though the channels need to be investigated in future research.

These changes in payer mix and utilization affected hospital finances. Medicaid reimbursed hospitals at greater rates than county programs and self-pay patients, thus increasing hospital revenue and operating margins. We find that 60–65 percent of incremental Medicaid spending either replaced spending by taxpayers or transferred funds to private hospitals in the form of greater reimbursements, with the remainder financing hospital care for self-pay patients or net incremental care.

We cannot reject the null hypothesis that there were no improvements in patient health even though patients became more likely to receive care at privately owned and better-quality hospitals. We argue that this reallocation of patient volume is

[42]Estimating equation (3a) with inpatient revenue as the outcome, we estimate an increase of $43,000 per bed. To isolate the price effect, we scale this down by 22 percent. Using the same model with uninsured stays per bed as the outcome, we find a decrease of 3.6 stays. Together, these two estimates imply an increase of $9,300 per avoided uninsured stay ($43\text{k} \times 0.78/3.6$). Following the same approach with outpatient revenue, we get an estimate of $230 per avoided uninsured visit. We observe a hospital use rate of 8 percent and an ER use rate of 20 percent by the uninsured in the NHIS. Applying these use rates, we get the population-level estimate ($9,300 × 8% = $744; $230 × 20% = $46). If we include the volume effect, the estimate increases to about $1,000 per change in uninsured rates.

demand driven, though our research design cannot distinguish supply and demand mechanisms, and we leave this exercise for future work.

Our study has three key limitations. First, our results on California may not reflect the experience of all expansion states. Second, we do not observe changes in care utilization outside hospitals. Third, since we observe only three years of data following the Medicaid expansion, our results should be interpreted as short-term effects.

Since the effects that we estimate for patients and hospitals were driven primarily by the expansion of Medicaid, these results take on additional significance when one considers that more than a dozen states have recently followed California's lead (as well as that of 24 other states) in 2014 and elected to expand their Medicaid programs. An additional 14 states have, as of this date, not expanded their Medicaid programs. The variation across states in decisions likely partially reflects uncertainty about the effects. We help fill this evidence gap as more states consider whether to expand public health insurance in the years ahead.

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